Journal of Cleaner Production 225 (2019) 833–856

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Modelling carbon emission intensity: Application of artificial neural network

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A R T I C L E I N F O

Article history:
Received 1 December 2018
Received in revised form
11 February 2019
Accepted 31 March 2019
Available online 5 April 2019

Keywords:
Carbon emissions
Artificial neural network
Forecasting
Sensitivity

A B S T R A C T

This study applies an artificial neural network (ANN) to develop models for forecasting carbon emission intensity for Australia, Brazil, China, India, and USA. Nine parameters that play an essential role in contributing to carbon emissions intensity were selected as input variables. The input parameters are economic growth, energy consumption, R&D, financial development, foreign direct investment, trade openness, industrialisation, and urbanisation. The study used quarterly data which span over the period 1980Q1-2015Q4 to develop, train and validate the models. To ensure the reproducibility of the results, twenty simulations were performed for each country. After numerous iterations, the optimal models for each country were selected based on predefined criteria. A 9-5-1 multi-layer perceptron with back-propagation algorithm was sufficient in building the models which have been trained and validated. Results from the validated models show that the predicted versus actual values indicate approximately zero errors along with higher coefficients of determination (R^2) of 0.80 for Australia, 0.91 for Brazil, 0.95 for China, 0.99 for India and 0.87 for USA. The Partial Rank Correlation Coefficient (PRCC) results reveal that for Australia, R&D has the highest sensitivity weight while for Brazil and the USA, urbanisation has the highest sensitivity weight. For China, population size has the highest sensitivity weight while energy consumption has the highest sensitivity weight in India. The ANN models presented in this study have been validated and reliable to predict the growth of CO_2 emission intensity for Australia, Brazil, China, India, and USA with negligible forecasting errors. The models developed from this study could serve as tools for international organisations and environmental policymakers to forecast and help in climate change policy decision-making.

1. Introduction

This study sought to use Artificial Neural Network (ANN) to develop models for forecasting carbon emission intensity for Australia, Brazil, China, India, and the USA. Global warming has been the most challenging environmental issue in the history of humanity (Acheampong, 2018). Thus, the increasing concentration of greenhouse gases in the atmosphere leading to global warming has severe implications for both economic and human development. Carbon dioxide is the primary greenhouse gas behind global warming. Therefore, efforts by international organisations to mitigate the adverse effect of global warming have been a focus on policies to reduce carbon emissions (Tamazian et al., 2009). Global carbon emissions have been increasing despite the global effort to reduce it. According to the International Energy Agency (2018) report, global energy-related carbon emissions increased by 1.4% in 2017. This represents an absolute increase of 460 million tons (Mt) reaching a historic high of 32.5 gigatons (Gt) for the past three years after remaining flat. This astronomic increase in carbon emissions conflicts with the Paris agreement on climate change to reduce carbon emissions.

While the global economy has witnessed an increase in carbon emissions, countries such as the USA, UK, Mexico, and Japan have experienced a sharp reduction in carbon emissions in 2017. For instance, carbon emissions dropped by 0.5% representing 25 Mt to 4810 Mt in the USA (International Energy Agency, 2018). On the other hand, the role of the Asia economies in carbon emissions cannot be underestimated. Two-third of global carbon emissions

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https://doi.org/10.1016/j.jclepro.2019.03.352
0959-6526/

Nomenclature

AD	Absolute deviation
ANN	Artificial neural network
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
$bias_k$	biases of the kth hidden neuron
BP	back-propagation
CI	confidence interval
CO_2	Carbon emission intensity
e^{-y}	exponential function
ENER	Energy consumption
FD	Financial development
FDI	Foreign direct investment
FFMLP	feedforward multilayer perceptron
GDP	Gross Domestic Product
GM	Grey Model
Gt	gigatons
IMF	International Monetary Fund
INDUS	Industrialisation
MAD	mean absolute deviation
$\max(y)$	maximum observation
ME_y	mean error on prediction
$\min(y)$	minimum observation
MLP	multi-layer perceptron
MSE	mean squared error
MSE_{test}	mean squared error on test dataset
MSE_{train}	mean squared error on training dataset
Mt	million tons
N^h	number of neurons in the hidden layer
N^i	number of input parameters
N^o	number of output parameters
N^{tr}	number of training samples
O_1	Output
P_{mean}	population mean
POP	Population
PRCC	Partial Rank Correlation Coefficient
R&D	Research and Development
R^2	Coefficients of determination
ReLU	rectifier function
RNN	recurrent neural network
SD	standard deviation
SE	standard error
SVR	support vector regression
TRAD	Trade Openness
URB	Urbanisation
x_{stand}	standardisation
y	observation for the output parameter
$\bar{y}$	mean of the CO_2 intensities
y_a	actual CO_2 intensity
y_{norm}	normalization
y_p	predicted CO_2 intensity

Greek letters

$\theta_r(x)$	rectifier function
$\theta_s(y)$	sigmoid function
μ	mean of the observations
σ	standard deviation of the observations

Subscript

i	input data (0, 1, 2, 3, 4, ….n)
j	jth input parameter

Superscript

$bias_o$	bias of the output neuron
H_k	kth hidden neurons
I_j	Input value of jth input parameter
n	number of input data
q	numbers of input parameters (closed-form formula)
r	number of hidden neurons (closed-form formula)
$w^{ih}_{j,k}$	weight of the link between I_j and H_k
$w^{ho}_{k,1}$	weight of the link between H_k and O_1

comes from Asian countries. Specifically, China and India are major players contributing to the increase in global carbon emissions. In the recent report by International Energy Agency (2018), carbon emissions increase from China increased by 9.1 gigatons in 2017 which is 1% higher than the level of emissions in 2014. Additionally, India experienced per-capital emissions of 1.7t CO_2. Southeast Asian has also contributed significantly to global emissions, with Indonesia playing a major in this region.

Understanding the future trend of carbon emissions at the global, regional, and national level could provide insight for developing appropriate environmental policies and strategies to mitigate carbon emissions. Thus, developing a reliable model for predicting the growth of carbon emissions could serve as the tool for international organisations and environmental policymakers to design and implement appropriate environmental policies and strategies to control environmental problems. Over the decades, some researchers have used classical statistical and econometric approaches to model or forecast the growth of carbon emissions. For instance, regression analysis has been the most popular estimation technique to study the causal relationship between carbon emissions and other independent variables such as economic growth, population, energy consumption, technology, globalisation and among others (see for example, Ahmad et al., 2017; Ahmed et al., 2017; Al-Mulali et al., 2016; Almeida et al., 2017; Grossman and Krueger, 1995; Köne and Büke, 2010). However, the effectiveness of regression depends on the reliability and availability of independent variables (Zhou et al., 2006). Additionally, given that variables for modelling carbon emissions are chaotic, non-stationary, and non-linear, the classical statistical and econometric approaches are not suitable for modelling such a complex behaviour (Gallo et al., 2014; Hussain and Reynolds, 1975; Stanley, 1997).

In addition to the statistical and regression approaches, some scholars have also employed time series models such as Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Moving Average (ARMA) to forecast emissions. For accurate forecasting using ARIMA and ARMA models, a large number of historical observation for the variable of interest is required (Pao et al., 2012; Zhou et al., 2006). Other researchers have also employed the Grey Model (GM) prediction especially, GM (1, 1) to forecast carbon emissions (see Ding et al., 2017; Lin et al., 2011; Pao and Tsai, 2011; Safa, Nejat, Nuthall and Greig, 2016; Wu et al., 2015). Generally, GM performs best with limited data (Yin and Tang, 2013). However, the forecasting accuracy of the GM (1, 1) has been questioned (see Zhou et al., 2006). Additionally, comparative studies have shown that ANN produces superior forecasting results relative to ARIMA, ARMA, classical statistical and regression approaches (Falat and Pancikova, 2015; Kohzadi et al., 1996; Prybutok et al., 2000; Stamenković et al., 2015; Valipour et al., 2013).

The forecasting ability of ANN has made it received a widespread application in the field of engineering (Ahmadi, 2011; Ahmadi et al., 2015; Valipour et al., 2013), agriculture (Khoshroo et al., 2018; Safa et al., 2016; Safa and Samarasinghe, 2011; Soltanali et al., 2017), energy (Deb et al., 2017; Debnath and Mourshed, 2018; Jebaraj and Iniyan, 2006), and finance (Kara et al., 2011; Moghaddam et al., 2016). One of the main advantages of ANN is its ability to use prior information to model a complex non-linear system, and its forecast results are robust since it can approximate non-linear input-output relationship to any degree of accuracy in an iterative manner (Safa and Samarasinghe, 2011; Sözen, 2009). Also, ANN can handle noisy data, accommodating multiple variables with non-linear, linear, and unknown interactions and make a good generalisation (Colwell, 1994; Hagan et al., 1996; Safa and Samarasinghe, 2011). Despite the forecasting ability of ANN, its application for forecasting carbon emissions intensity is still limited (see Zhao et al., 2018). Therefore, this study utilised ANN to develop models for forecasting carbon emissions intensity for Australia, Brazil, China, India, and USA. These countries are studied because they are among the top carbon-emitting countries.

In this direction, this study makes several distinct contributions to a new body of knowledge: Firstly, unlike the previous studies which have forecasted carbon emissions using only economic growth and population as input variables (see Pao et al., 2012; Pao and Tsai, 2011; Zhao and Du, 2015), this study incorporates other variables such as energy consumption, R&D, financial development, FDI, trade openness, industrialisation, and urbanisation, which play important role in contributing to carbon emissions, in our model to prevent underestimation of carbon emissions intensity. Secondly, unlike the previous forecasting studies on emissions, this study utilises the Partial Rank Correlation Coefficient (PRCC) to conduct sensitivity analysis to determine the input variable that is most influential in contributing to carbon emissions for the respective countries. Khoshroo et al. (2018), Marino et al. (2008) and Saltelli and Marivoet (1990) argue that PRCC is the most reliable and efficient method for sensitivity analysis. Additionally, unlike previous studies, this study uses high-frequency data to provide accurate forecasting models. Finally, given that this study focuses on the major carbon-emitting countries, the models that will be developed from this study would help environmental planners in climate change policy decision-making.

The remaining sections are organised as follows. Section 2 provides a literature review while section 3 provides an overview of the research methodology and data, followed by results and discussions in section 4. Section 5 also presents the proposed closed-form formula for forecasting carbon emissions intensity while section 6 presents the sensitivity analysis. Conclusions and policy implications are presented in section 7.

2. Determinants of carbon emissions

In this section, we provide a brief overview of the literature that supports the variables that were used as inputs for the modelling. Following the existing literature, we explore the impact of economic growth, energy consumption, population size, R&D, urbanisation, globalisation (FDI and trade openness) and industrialisation on carbon emissions. For clarity purpose, the literature is divided into the following segments: economic growth–carbon emissions nexus, energy consumption–carbon emissions nexus, population size–carbon emissions nexus, R&D–carbon emissions nexus, urbanisation–carbon emissions nexus, financial development–carbon emissions nexus, industrialisation–carbon emissions nexus and globalisation (FDI and trade openness)–carbon emissions nexus.

2.1. Economic growth-carbon emissions nexus

Economic growth is argued to be the primary force behind the persistent increase in global environmental pollution (carbon emissions). The nexus between economic growth and carbon emissions have been widely studied. Some scholars are of the view that economic growth has an adverse effect on the environment by increasing carbon emissions (Grove, 1992) while others contend that economic growth is necessary to improve the quality of the environment (Meadows et al., 1992). Majority of the studies on the nexus between economic growth and carbon emissions is much rooted in the Environmental Kuznets Curve (EKC) hypothesis[1]. The EKC hypothesis assumes that an inverted U-shaped relationship exists between economic growth and carbon emissions. Thus, at the early stages of economic growth, carbon emissions increase, but beyond a certain level of economic growth, carbon emissions reduces (Grossman and Helpman, 1991; Grossman and Krueger, 1995; Stern, 2004). Findings from the empirical studies on the impact of economic growth on carbon emissions remain highly contentious. For instance, Ahmad et al. (2017) studied the nexus between economic growth and carbon emissions in Croatia using ARDL and the results reveal that inverted U-shape relation between carbon emissions and economic growth in the long run and this supports the EKC hypothesis. The Granger causality based on the VECM approach shows that bi-directional causality exists between carbon emissions and economic growth in the short run and unidirectional causality from economic growth to carbon emissions in long run.

For the case of Asia economies, Apergis and Ozturk (2015) employed the GMM to examine the nexus between economic growth and carbon emissions. The results confirm the validity of the EKC hypothesis. Similarly, Narayan and Narayan (2010) used panel cointegration technique to investigate the relationship between economic growth and carbon emissions for 43 developing countries and their findings confirm the EKC hypothesis in Middle Eastern and South Asian countries while the EKC hypothesis was not confirmed in Africa, East Asia and Latin America. Using GMM, Tamazian and Bhaskara Rao (2010) found that the EKC hypothesis exists in transitional economies. In another study, Tamazian et al. (2009) found that economic growth degrades the environment by increasing carbon emissions. Additionally, Stern and Common (2001) and Stern (2004) found that carbon emissions monotonically increases with economic growth, which does not confirm the EKC hypothesis. Similarly, using GMM-PVAR, the empirical findings of Acheampong (2018) revealed that economic growth reduces carbon emissions at the global level and Caribbean-Latin America countries while it has an insignificant effect on carbon emissions for countries in sub-Saharan Africa, Asia-Pacific and the Middle East and North Africa (MENA). Using data from Malaysia, Saboori et al., (2012) revealed that the EKC hypothesis exists. In China, Liu and Bae (2018) found that economic growth increases carbon emissions.

2.2. Energy consumption-carbon emissions nexus

The Kaya identity shows that one of the key factors that influence the evolution of carbon emissions in the intensity of energy consumption (see Acheampong, 2018). Additionally, the International Energy Agency (2018) report further suggests that energy intensity is one of the two drivers of carbon emissions, the other being carbon intensity. While global carbon intensity declined less in 2017 than in 2016, the rate remains similar to the

[1] For literature on the nexus between carbon emissions and economic growth see the extensive literature survey of (Dinda, 2004).

average rate of improvement in 2014–2016 – partly driven by the increasing expansion of renewables. However, the slower improvement in the energy intensity of energy demand in 2017 was not sufficient to counteract the effect of higher economic growth, leading to the increase in global energy-related carbon emissions in 2017 (International Energy Agency, 2018). The empirical literature suggests that energy consumption has an important impact on carbon emissions. For instance, using data from China, Zhang and Cheng (2009) reported that energy consumption increases carbon emissions. Similarly, Shahbaz et al. (2013) reported that energy consumption increases carbon emissions in Indonesia. Also, using data from Kuwait, Salahuddin et al., (2018), revealed that energy consumption increases carbon emissions. Similarly, using data from 14 MENA countries, Omri (2013) reported that energy consumption increases carbon emissions. Focusing on Bangladesh, Jahangir et al., (2012) reported that energy consumption increases carbon emissions. Similarly, Halicioglu (2009) reported that energy consumption stimulates carbon emissions in Turkey. The results of Begum et al. (2015) also revealed that energy consumption stimulates carbon emissions in Malaysia. Using data from China, the empirical findings of Wu et al. (2016) revealed that energy consumption increases carbon emissions.

2.3. Population-carbon emissions nexus

Population size, which refers to the total number of people living in a particular country, has an important effect on carbon emissions. In almost all climate models, population size is the only demographic variable considered (Zhu and Peng, 2012). In a classical study, Birdsall (1992) argue that population size affects carbon emissions through energy use and deforestation. Additionally, population size could influence the scale and structure of consumption and production, thereby increasing carbon emissions (Zhu and Peng, 2012). The empirical findings of Zhu and Peng, (2012) revealed that population size has no significant impact on carbon emissions but it is population structure, population age and household size that matter. Using data from 93 countries, the findings of Shi (2003) revealed that population size is proportionally related to the growth of carbon emissions. Using data from Europe, Weber and Sciubba (2018) reported that the population growth rate has a considerable effect on carbon emissions is Western Europe but has a negligible effect on carbon emissions in Eastern Europe. Focusing on Malaysia, the findings of Begum et al. (2015) revealed that the population growth rate has no effect on carbon emissions. Using 128 countries, Dong et al. (2018) reported that population size contributes significantly to the growth of carbon emissions.

2.4. R&D-carbon emissions nexus

Technological innovation is another important variable that influences the environment (carbon emissions). Technological innovation could be helpful in switching to more sustainable sources of energy including renewables which could reduce carbon emissions (Shahbaz et al., 2018). Shahbaz et al. (2018) further argue that innovation related to energy is more prone to influence energy consumption and, hence, carbon emissions, specifically energy innovations which are intuitively more relevant and important for environmental quality. However, investment in research and development (R&D) is crucial for facilitating the promotion of technological progress, which could lead to greater efficiency in energy and the use of natural resources, thereby reducing carbon emissions (Awaworyi Churchill et al., 2019). On the other hand, the positive effect of R&D on economic growth and trade could increase carbon emissions through the scale effect of larger production associated with economic growth and trade liberalisation (Awaworyi Churchill et al., 2019). In an empirical study, Tamazian et al. (2009) reported that R&D contributes to the mitigation of carbon emissions in BRICS. The study of Awaworyi Churchill et al. (2019) also revealed that R&D reduces carbon emissions in G7 countries. Using data from France, Shahbaz et al. (2018) reported that R&D contributes to the reduction of carbon emissions. Fernández-Fernández et al. (2018) also used data from the European Union (15), the United States and China; their results revealed that R&D contributes to the reduction of carbon emissions. Using data from China, Zhang et al., (2017), R&D is conducive for reducing carbon emission. On the other hand, Jiao et al. (2018) found that R&D generally increases carbon emissions; however, considering regional effects, R&D reduces carbon emissions.

2.5. Urbanisation-carbon emissions nexus

Urbanisation may also play important role in the evolution of carbon emissions. The theoretical linkage between urbanisation and environmental quality has been discussed in the work of (Poumanyvong and Kaneko, 2010) and (Sadorsky, 2014). Ecological modernization theory, urban environmental transition theory and compact city theory are the major theories for explaining the impact of urbanisation on the environment (Poumanyvong and Kaneko, 2010; Sadorsky, 2014). The ecological modernization theory discusses the impact of urbanisation on the environment at the national level while the latter theories focus the impact at the city level (Poumanyvong and Kaneko, 2010). The ecological modernization theory argues that environmental problems increase as society becomes modernize and thereafter, seek to address environmental problems at the advanced stage of economic development. Thus, as a society makes transition from low-level of economic development to an intermediate level of development, environmental problems increases; however, at the advanced stage of economic development with efficient technology, urban agglomeration and knowledge spillover effect, societies seek to minimize environmental problems such as mitigating carbon emissions (Gouldson and Murphy, 1997; Mol and Spaargaren, 2000; Poumanyvong and Kaneko, 2010).

Similar to the ecological modernization theory, the urban environmental transition theory also argues that environmental problems differ across different stages of economic development at the city level (McGranahan, 2010). Thus, as cities become prosperous by increasing production, environmental problems also increase; however, as cities become wealthier or at the advanced stage of development, environmental problems reduce as results of improvement in environmental regulation, technological progress and structural change in the economy (Poumanyvong and Kaneko, 2010; Sadorsky, 2014). As ecological modernization and the urban environmental transition theories argue for both negative and positive effect of urbanisation on the environment, the net effect of urbanisation on the environment is indeterminate (Sadorsky, 2014). On the other hand, the compact city theory focuses on the positive externality of urbanisation on the environment. Thus, rapid urbanisation help cities to facilitate economies of scale for urban infrastructure and these economies of scale reduces environmental pollution (Poumanyvong and Kaneko, 2010). Thus, high urban density helps to reduce travel distance, car dependency, energy consumption and carbon emissions (Burton, 2000; Capello and Camagni, 2000). However, some scholar argues that increasing urbanisation could result in traffic congestions and overcrowding which will consequently increase energy consumption and carbon emissions (Breheny, 2001; Poumanyvong and Kaneko, 2010; Rudlin and Falk, 1999). Empirically, Poumanyvong and Kaneko, (2010) found that urbanisation increases carbon

emission. Using data from emerging countries, Sadorsky (2014) found that urbanisation could either increase or reduce carbon emissions depending on the estimator. Using data from China, Wang et al. (2016) reported that urbanisation contributes to the growth of carbon emissions. Similarly, Zhang and Lin (2012) reported that urbanisation increases carbon emissions in China. Additionally, using data from China, the findings of Wu et al. (2016) revealed that urbanisation increases carbon emissions. Using data from 23 European countries, Al-Mulali et al. (2015) found that urbanisation increases carbon emissions. Liu and Bae (2018) further found that urbanisation contributes to the increased carbon emissions in China. Contrarily, Bekhet and Othman (2017) found that urbanisation contributes to carbon emissions. They further found that an inverted U-shaped relationship exists between urbanisation and carbon emissions.

2.6. Financial development-carbon emissions nexus

Recently, research on the nexus between financial development and carbon emissions has received interest among energy and environmental economists. It is argued that financial development could reduce carbon emissions, as it attracts foreign direct investment and further promotes research and development, which in turn enhance the quality of the environment (Tamazian et al., 2009). On the other hand, financial development could worsen the quality of the environment by increasing carbon emissions (Sadorsky, 2010, 2011). argues that a developed financial system makes it easy for economic agents to have access to cheap credits to purchase big-ticket items and expand their existing plants, which increase energy consumption, thereby increasing carbon emissions. While it is argued theoretically that the impact of financial development could either improve or worsens the environment, the empirical findings remain ambiguous. For instance, one category of empirical findings report that financial development reduces carbon emissions (see Al-Mulali et al., 2015; Tamazian and Bhaskara Rao, 2010; Tamazian et al., 2009) while the second category report that financial development simulates the growth of carbon emissions (see Boutabba, 2014; Sehrawat et al., 2015; Shahbaz et al., 2016). The third category of the empirical literature also suggests that financial development has no relationship with carbon emissions (see Dogan and Turkekul, 2016; Maji et al., 2017; Omri et al., 2015).

2.7. Industrialisation-carbon emissions nexus

Industrialisation, which is a critical path to economic and social modernization, has a significant impact on the environment. Industrialisation refers to an increase in industrial activity, and that rapid industrialisation leads to higher energy usage because higher value-added manufacturing uses more energy than does traditional agriculture or basic manufacturing (Sadorsky, 2013). In other words, industrialisation promotes the rapid growth of fossil fuel consumption and produces significant amounts of carbon dioxide and other greenhouse gas emissions (Li and Lin, 2015). Using data from China, Wang et al. (2011) reported that industrialisation increases carbon emissions. Similarly, Liu and Bae (2018) found that industrialisation increases the intensity of carbon emissions in China. Using data from MENA countries, the empirical results of Al-Mulali and Ozturk (2015) revealed that industrialisation contributes to the increase in carbon emissions. Using data from China, Zhou et al., (2013) found that industrialisation reduces carbon emissions. The empirical results of Li and Lin (2015) revealed that across all income groups, industrialisation fuel the growth of carbon emissions.

2.8. Globalisation-carbon emissions nexus

The role of foreign direct investment (FDI) and trade openness on the environment has been highly debated in the literature. Trade openness impact on the environment through the scale effect, technique effect and composition effect (Antweiler et al., 2001; Ghani, 2012). The scale effect of trade openness on the environment occurs through the growth of the economy. Thus, the scale effect suggests that trade openness facilitate economic growth which in turn result in higher carbon emissions. Additionally, the technique effect suggests that trade openness promotes the transfer of environmentally friendly technologies which could result in reducing carbon emissions. According to the composition effect, trade openness could affect the environment by changing the structure of the economy. In addition, FDI could improve or worsen environmental quality. Studies on the impact of FDI on the environment (carbon emissions) are deeply rooted in the Pollution-haven hypothesis, Pollution-halo hypothesis and scale effect hypothesis (Pao and Tsai, 2011). According to the pollution haven, FDI degrades the quality of the environment by increasing carbon emissions. Thus, weak environmental regulation in a host country could attract the inflow of FDI by multinational companies that are pollution intensive, thereby increasing carbon emissions (Shahbaz et al., 2018). Like the pollution-haven hypothesis, the scale effect hypothesis also suggests that the inflow of FDI could contribute significantly to a host countries' economic output, which in turn, increase carbon emissions (Pao and Tsai, 2011; Shahbaz et al., 2018). The pollution-halo effect hypothesis also suggests that FDI could reduce carbon emissions by increasing the spread the environmentally friendly technologies.

Empirically, Acheampong (2018) found that trade openness decreases carbon emissions at the global level, Asia-Pacific, MENA and Sub-Saharan Africa countries. Similarly, Shahbaz et al. (2013) found that trade openness improves environmental quality by reducing carbon emissions in South Africa. Antweiler et al. (2001) further reported that trade is important for improving the quality of the environment by reducing carbon emissions. Contrarily, Ren et al., (2014) found that trade increases carbon emissions in China. Using data from five South Asian countries, Ahmed et al. (2017) found that trade openness increases carbon emissions. Focusing on the impact of FDI on the environment, Shahbaz et al. (2015) found that at the global level, FDI increases carbon emissions. However, they concluded that the impact of FDI on carbon emissions is sensitive to income and regional groups. In France, Shahbaz et al. (2018) found that FDI increases carbon emissions. Similarly, Ren et al. (2014) found that FDI increases carbon emissions in China. Contrarily, using 19 of the G20 countries, Lee (2013) reported that FDI contributes to the reduction in carbon emissions.

3. Data and methodology

3.1. Dataset

The study used time series data which spans between 1980 and 2015. However, to develop accurate models, the study follows Sbia et al. (2014) and Shahbaz et al. (2017) to use quadratic-sum approach to convert the annual data from low-frequency data to high-frequency data. Therefore, quarterly data between 1980Q1-2015Q4 was used for the study. This period represented 144 quarters. Table 1 presents the proxies for the variables and the justification for selecting the input variables used for the modelling. In selecting the input variables, the study follows the literature on carbon emissions to select the fundamental variables that influence carbon emissions intensity. Except for financial development, all the remaining variables were sourced from World Bank (2016). The

Table 1
Variables for the study.

Variable	Code	Proxies	Definitions	Reference
Carbon emissions intensity	CO_2	CO_2 intensity (kg per kg of oil equivalent energy use)	Carbon emissions intensity is the volume of carbon emissions due to economic activity/economic growth. It is also defined as carbon emissions emitted per unit of energy consumed.	
Energy consumption	ENER	Energy use (kg of oil equivalent per capita)	Energy use refers to use of primary energy before transformation to other end-use fuels.	Destek and Sarkodie (2019); Sarkodie and Strezov (2018).
Financial development	FD	The financial development index is a broad-based measure which comprises bank-based and market-based indicators of financial development.	Financial development refers to the increased flow of foreign direct investment, banking and stock market activities.	Shahbaz et al. (2013); Tamazian and Bhaskara Rao (2010); Tamazian et al. (2009).
Foreign direct investment	FDI	Foreign direct investment, net inflows (% of GDP)	Foreign direct investment is the net inflows of investment to acquire a lasting management interest in an enterprise operating in an economy other than that of the investor.	Ren et al. (2014); Sarkodie and Strezov (2019); Zhang and Zhou (2016).
Economic growth	GDP	GDP per capita (constant 2010 US$)	GDP per capita is gross domestic product divided by midyear population. It is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products.	Ben Jebli et al, (2016); Grossman and Krueger (1995); Saboori et al. (2012).
Industrialisation	INDUS	Industry, value added (% of GDP)	Industrialisation refers to an increase in industrial activity. It comprises value added in mining, manufacturing, construction, electricity, water, and gas.	Wang et al. (2011);
R&D	R&D	Trademark applications, total	The R&D covers basic research, applied research, and experimental development.	Jiao et al. (2018); Shahbaz et al. (2018).
Population	POP	Population, total	Total population refers to the total number of people living in a particular geographical area. It is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship.	Zhu and Peng (2012)
Trade Openness	TRAD	Trade (% of GDP)	Trade is the sum of exports and imports of goods and services measured as a share of the gross domestic product.	Acheampong (2018); Ren et al. (2014)
Urbanisation	URB	Urban population (% of total)	Urban population refers to people living in urban areas as defined by national statistical offices.	Poumanyvong and Kaneko (2010); Sadorsky (2014).

financial development index was obtained from the International Monetary Fund (IMF)[2]. Table 2 also presents the descriptive statistics for variables.

3.2. Methodology

3.2.1. Artificial neural networks

The study aims to develop models for predicting/forecasting carbon emissions intensity for high carbon-emitting countries such as Australia, Brazil, China, India, and USA. ANN is employed and incorporated in the proposed theoretical framework of the model as shown in Fig. 1a. The diagram (Fig. 1a) generally depicts the possible relationship connecting nine (9) determinants (inputs) of CO_2 emission intensity and CO_2 emission intensity (output) for the selected countries.

Artificial neural networks (ANNs) are data processing systems that mimic the way data is processed in the human brain (Boateng et al., 2019). An ANN is made up of input, hidden, and output layers which consist of numerous processing components called neurons (Boateng et al., 2019). The neurons process the data and feed forward to the subsequent layer. These neurons are connected by corresponding links between layers. On each connected link is a numeric weight. ANNs can automatically adjust their weights to enhance their behaviour, unlike statistical models (Boussabaine, 1996). The approach adopted in ANN does not require prior expertise in computer programming to develop and compute solutions as required in other numerical solutions (Ghritlahre and Prasad, 2018). A problematic issue in statistical model development is multicollinearity, i.e., the high degree of correlation among independent variables, which is much better dealt with in ANN because the assumption of independent variables being uncorrelated is not made (Detienne et al., 2003).

Moreover, statistical tools cannot deal effectively with nonlinearity while ANNs are inherently nonlinear nonparametric models that can deal with indefinable nonlinearity in a straightforward manner (Detienne et al., 2003). Also, ANNs are especially suitable to find solutions for problems that have fuzzy information and are highly complex where individuals usually make decisions on an intuitional basis (Ghritlahre and Prasad, 2018). Besides, unlike most statistical approaches, ANNs do not need predefined mathematical equations of the relationship between the model inputs and corresponding outputs (Shahin and Elchalakani, 2008). These enable ANNs to overcome the limitations of existing modelling methods. Despite the differences between ANNs and statistical approaches, both techniques can be combined into a solid and powerful methodological platform (Karlaftis and Vlahogianni, 2011). This is because ANN is like a 'black box' and hence lacks self-explanation. As expressed by Alaka et al. (2018 p. 173), 'the more accurate the tool, the less transparent the result.' Consequently, statistical approaches such as descriptive statistics are often incorporated to produce explanatory results that can easily be interpreted and understood.

ANN has become a popular and useful tool for modelling accurate predictions to solve complex and nonlinear problems in diverse industrial domains. Many researchers have used ANN in the field of energy utilization and conversion systems for performance predictions (Kalogirou, 2000), solar radiations predictions (Yadav and Chandel, 2014), length of stay predictions on post-coronary care units (Mobley et al., 1995), bankruptcy predictions (Adnan Aziz and Dar, 2006), and performance prediction of solid desiccant dehumidifier cooling methods (Jani et al., 2017). However, the application of ANN in environmental economics is quite rare.

3.2.2. Optimal model selection

The performance of a neural network model primarily depends on the architecture of the network and the tuning of various parameters. Fig. 1b illustrates a robust process used in selecting the

[2] http://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B.

Table 2
Descriptive statistics.

	Count	Mean	SD	Min	Max
Australia					
ENER	144	5268.8320	423.9819	4533.5690	5971.2290
FD	144	0.6808	0.2168	0.2731	0.9657
FDI	144	2.4624	1.7497	−4.3786	7.8503
GDP	144	41787.9100	8398.9680	29725.5000	55179.3500
INDUS	144	25.5816	1.1295	22.3563	29.3606
R&D	144	37201.0600	18086.5500	12935.0600	73741.6600
POP	144	18800000.0000	2610000.0000	14600000.0000	24000000.0000
TRAD	144	37.3866	4.7907	28.1058	46.2559
URB	144	16400000.0000	2540000.0000	12500000.0000	21500000.0000
CO_2	144	3.1120	0.1100	2.8758	3.3627
Brazil					
ENER	144	1084.3660	166.5520	870.0903	1494.8180
FD	144	0.4030	0.1575	0.1713	0.6273
FDI	144	2.0784	1.4981	0.0883	5.1136
GDP	144	9109.4750	1362.5440	7192.9950	11961.0800
INDUS	144	29.1012	8.1757	18.8637	43.1403
R&D	144	88282.5300	37664.9800	27442.0600	164319.7000
POP	144	167000000.0000	25600000.0000	120000000.0000	207000000.0000
TRAD	144	21.2789	4.5309	14.2097	29.8731
URB	144	132000000.0000	29700000.0000	78200000.0000	177000000.0000
CO_2	144	1.5872	0.0987	1.3841	1.7763
China					
ENER	144	1103.4160	518.0744	596.2954	2238.4880
FD	144	0.4056	0.1301	−0.0559	0.6458
FDI	144	2.9237	1.6337	0.2046	6.7016
GDP	144	2161.0150	1822.3990	345.7698	6642.6710
INDUS	144	44.9490	1.9043	39.8404	49.0031
R&D	144	430376.7000	543678.5000	18218.9100	2206486.0000
POP	144	1210000000.0000	120000000.0000	977000000.0000	1370000000.0000
TRAD	144	36.8526	14.2636	12.0060	64.6305
URB	144	437000000.0000	174000000.0000	186000000.0000	770000000.0000
CO_2	144	3.0654	0.2692	2.4261	3.4830
India					
ENER	144	414.3776	95.8066	283.4874	654.1635
FD	144	0.3230	0.0974	0.1857	0.4696
FDI	144	0.8444	0.9051	−0.0012	3.7726
GDP	144	818.1663	392.8301	382.6152	1805.4140
INDUS	144	28.7170	1.4005	25.9435	31.7937
R&D	144	80968.1400	70535.7400	14350.7800	300555.9000
POP	144	1010000000.0000	186000000.0000	691000000.0000	1310000000.0000
TRAD	144	28.9482	14.8495	12.2991	56.5884
URB	144	282000000.0000	79600000.0000	159000000.0000	432000000.0000
CO_2	144	2.1817	0.3280	1.5424	2.7770
USA					
ENER	144	7562.8570	351.4622	6692.1100	8074.1540
FD	144	0.7201	0.1951	0.2862	0.8938
FDI	144	1.2952	0.7862	0.2494	3.7214
GDP	144	41135.7900	7427.4450	28281.2400	52366.9900
INDUS	144	20.9829	0.7909	18.9394	23.4137
R&D	144	195258.0000	99127.9600	45927.1300	389988.5000
POP	144	274000000.0000	29400000.0000	226000000.0000	322000000.0000
TRAD	144	22.9258	4.3746	16.4905	31.2702
URB	144	214000000.0000	30000000.0000	167000000.0000	263000000.0000
CO_2	144	2.4977	0.0563	2.3631	2.6313

optimal predictive models for the five countries. Details of the whole process are explained in the proceeding sections.

3.2.3. Development of ANN models

Due to the severe computations on the high dimensional data when training the ANN, features of the data set are scaled using standardisation (x_{stand}) and normalization (y_{norm}) on the inputs and output data respectively (Boateng et al., 2019). In normalization, the observations range from $0 \leq y_{norm} \leq 1$ to increase the rate of training the network. Hence, the output variable (CO_2 intensity) is normalised for each country, as it further facilitates the use of the sigmoid function for the output layer. Normalization is expressed in Eq. (1):

$$y_{norm} = \frac{y - \min(y)}{\max(y) - \min(y)} \tag{1}$$

Where y is the observation for the parameter, min(y) and max(y) is the minimum and maximum observations respectively. Standardisation is expressed in Eq. (2):

$$x_{stand} = \frac{x - \mu}{\sigma} \tag{2}$$

Where μ is the mean of the observations for the parameter and σ is the standard deviation of the observations for the parameter. Standardisation tends to centre the input values towards zero (0). Standardising the input data into a lesser array of variability would

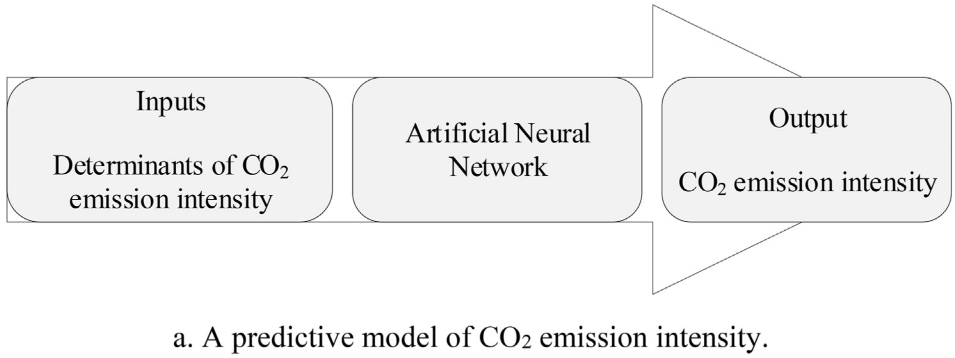

Fig. 1a. A predictive model of CO_2 emission intensity.

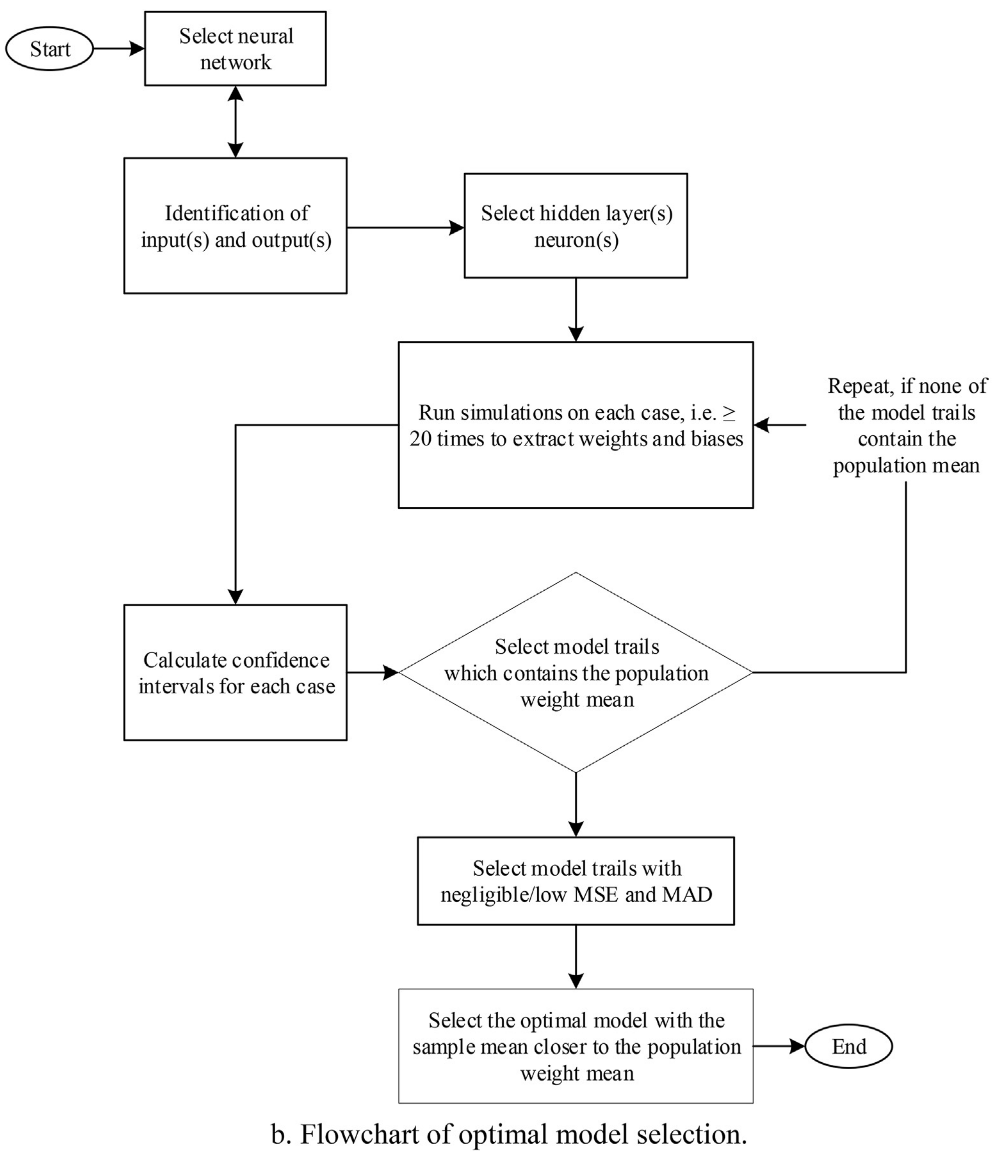

Fig. 1b. Flowchart of optimal model selection.
Source: Authors' construct.

likely aid the effective learning of the neural network while improving the numerical state of the optimisation problem (StatSoft Inc., 2008). Thus, scaling the data eliminates any instances of one variable dominating the other (Boateng et al., 2019). The 144 observations for individual countries (Australia, Brazil, China, India, and USA) were randomly split into training and test sets to ensure

the reliability of the results over time. 80% (115 observations) of the data set were used for training the model, while the remaining 20% (29 observations) were used to validate the model. Similar data ratio has been commonly used in previous studies (see Abidoye and Chan, 2018; Lam et al., 2008; Morano et al., 2015).

Afterwards, a multi-layer perceptron (MLP) with back-propagation (BP) is selected to achieve the optimal performance of the ANN model. MLP is the most commonly used neural network (Ghaedi and Vafaei, 2017; Pérez-Sánchez et al., 2016). The BP algorithm was selected as the learning algorithm. The BP algorithm is often used to iteratively minimize the cost function concerning the interconnection weight and neurons thresholds (El Kadi, 2006; Kartalopoulos and Kartakapoulos, 1997). Therefore, the MLP with a BP algorithm can approximate any continuous function to meet the desired accuracy (Patel and Jha, 2015). The sigmoid function, which ranges from 0 to 1, was selected as the activation function for the output layer while the rectifier function (ReLU) was used as the activation function for the hidden layer to perform efficient computations. Currently, the ReLU is the most popular activation function for deep neural networks (LeCun et al., 2015) while the sigmoid function is the most popular activation function for ANNs (Alvanitopoulos et al., 2010). The sigmoid and rectifier functions are defined as Eqs. (3) and (4) respectively;

$$\theta_s(y) = \frac{1}{1 + e^{-y}} \tag{3}$$

$$\theta_r(x) = \ max(0, x) \tag{4}$$

Where $\theta_s(y)$ is the sigmoid function, $\theta_r(x)$ is the rectifier function, and e^{-y} is the exponential function.

4. Results and discussion

4.1. Training of models

In training the neural network, the selection of the hidden layer neurons is crucial to the performance of the model (Boateng et al., 2019). The optimum number of hidden layer neurons generally has to be found using a trial and error approach (Maier and Dandy, 2001). However, some general guidelines may be followed. Hecht-Nielsen (1987) suggests the following upper limit for the number of hidden layer nodes in order to ensure that the neural network can approximate any continuous function. The upper limit of the number of hidden layer nodes is calculated using Eq. (5):

$$N^h \le 2N^i + 1 \tag{5}$$

Where N^h is the number of neurons in the hidden layer and N^i is the number of input parameters. For this present study, with nine (9) input parameters, the upper limit of the number of neurons in the hidden layer is given in Eqs. (6) and (7):

$$N^h \le 2(9) + 1 \tag{6}$$

$$N^h \le 19 \tag{7}$$

From this, the number of hidden layer neurons should not be more than 19. However, in order to ensure that the network does not overfit the training data, the relationship between the number of training samples and network size also needs to be considered (Maier and Dandy, 2001). Overfitting is where the model performs well on the training data but poorly on the test/validation data, and underfitting is where the model performs well on the test data and poorly on the training data. Rogers and Dowla (1994) recommend the following upper limit for the number of hidden layer nodes to satisfy the above criteria using Eq. (8):

$$N^h \le \frac{N^{tr}}{N^i + 1} \tag{8}$$

Where N^{tr} is the number of training samples. Consequently, the upper limit for the number of hidden layer neurons may be taken as the smaller of the values for N^h obtained from the two formulas. For this present study, with 115 training samples, the upper limit of the number of hidden layer is given in Eqs. (9) and (10);

$$N^h \le \frac{115}{9 + 1} \tag{9}$$

$$N^h \le 11.5 \sim 12 \tag{10}$$

From this, the number of neurons in the hidden layer should not be more than 12. Consideration should be given to the selection of the hidden layer neurons since it affects the architecture of the network as well as the accuracy. If the network architecture is too complex, overfitting may occur, and if the architecture is too simple, the preferred estimate skill may not be achieved (Hippert et al., 2001). From experimentations and practice, the problem could be argued as trivial. Therefore, the hidden layer neurons required in an MLP with a single layer could further be determined using a simplified formula, Eq. (11):

$$N^h = \frac{N^i + N^o}{2} \tag{11}$$

$$N^h = \frac{9 + 1}{2} \tag{12}$$

$$N^h = 5 \ Hidden \ layer \ neurons \tag{13}$$

Where N^o is the number of output parameters. From the computation, five (5) neurons in the hidden layer were deemed optimal in configuring the neural networks for this study. As a result, a 9-5-1 MLP with BP was sufficient to perform the necessary predictive capabilities with a minimal/negligible error. Fig. 2 illustrates the configuration of the three-layer feed-forward MLP.

At this stage, a stochastic gradient descent batching is applied to the entire neural network to find the optimal weights. The 9-5-1 MLP for each country is trained a number of times to update its weights after every 5 observations. The stochastic gradient descent is initialized to improve the accuracy and minimize the loss over the various rounds (Boateng et al., 2019). During the training of the neural network, there is some randomness involved because at the start of training the weights would be randomly initialized. This sort of randomization results in different results at various iterations. To ensure stable results (reproducibility) each time the weights are initialized, a robust approach is employed by conducting repeated evaluation experiments (Boateng et al., 2019). In this approach, each case is run at least 20 times with different random weights at the start and then the mean is taken to calculate confidence intervals (CIs). The accuracies, means, standard deviations (SDs), standard errors (SEs), and intervals are evaluated to estimate the skill of the stochastic model at a 95% confidence interval while simultaneously checking the mean squared errors (MSEs) on both the training and test sets. The MSE metric is used since it is very closely related to the forecast accuracy. The MSEs are determined using Eq. (14):

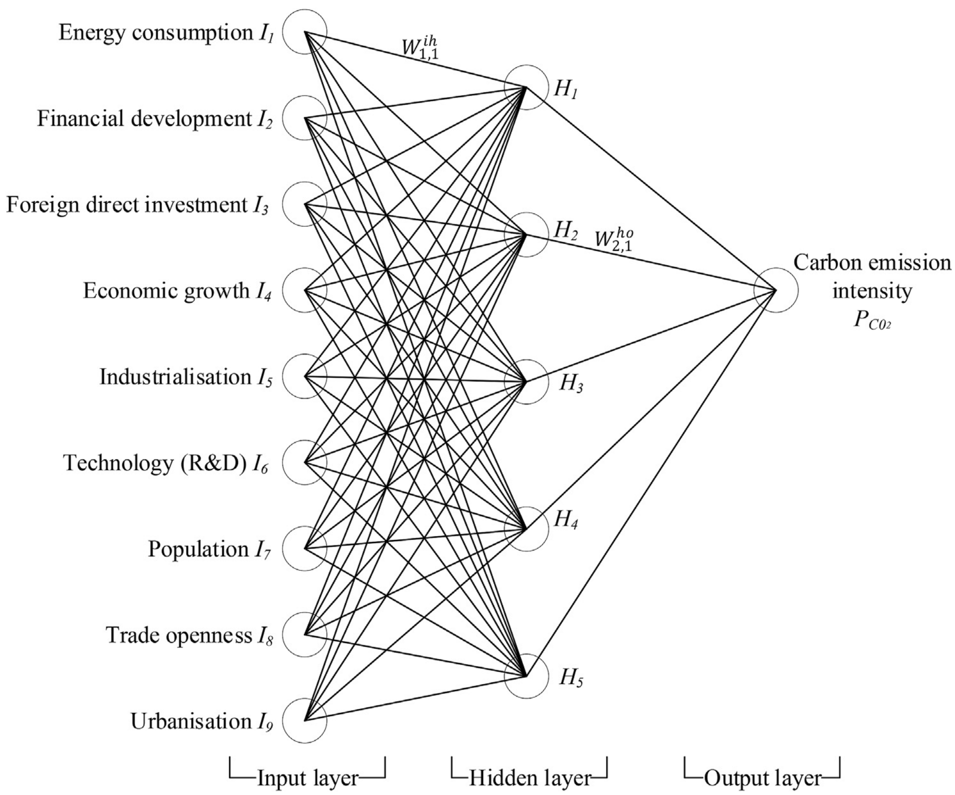

Fig. 2. Configuration of the developed neural network (9-5-1).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_a - y_p\right)^2 \tag{14}$$

Where n is the number of input data (i = 0, 1, 2, 3, 4, ….n), y_a and y_p are the actual and predicted CO_2 intensities respectively. For each country, the computed MSE on both the training and test sets are presented in Appendix Table Ia - Ie. Coefficient of determination (R^2) was further computed for each trial on the actual (independent) and predicted (dependent) CO_2 intensities for each country. The R^2 denotes the ratio of the change in the output parameter that is predictable from the input parameter. The R^2 coefficient ranges from 0 to 1, and a coefficient close to 1 depicts an excellent performance. R^2 is determined using Eq. (15):

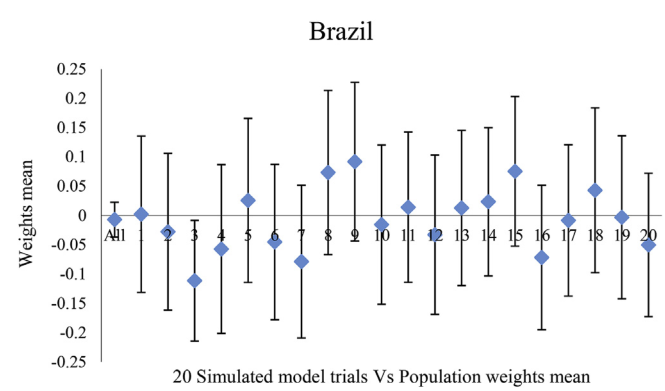

Fig. 3b. Point and interval estimates for 20 trials.

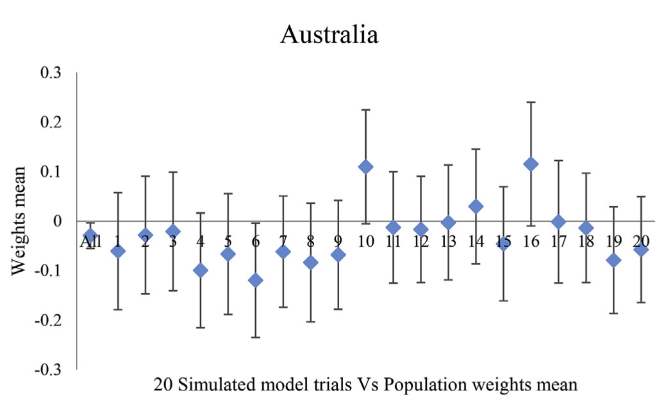

Fig. 3a. Point and interval estimates for 20 trials.

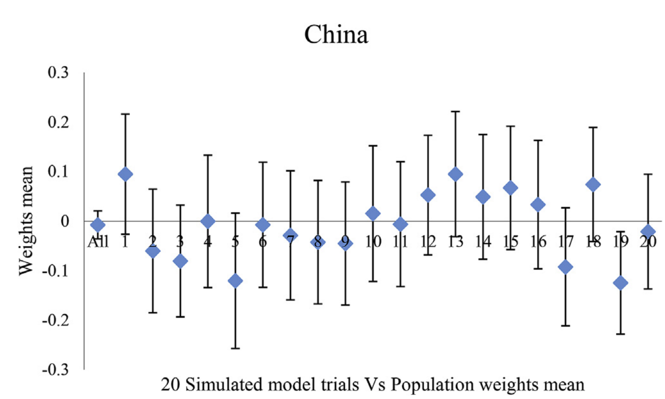

Fig. 3c. Point and interval estimates for 20 trials.

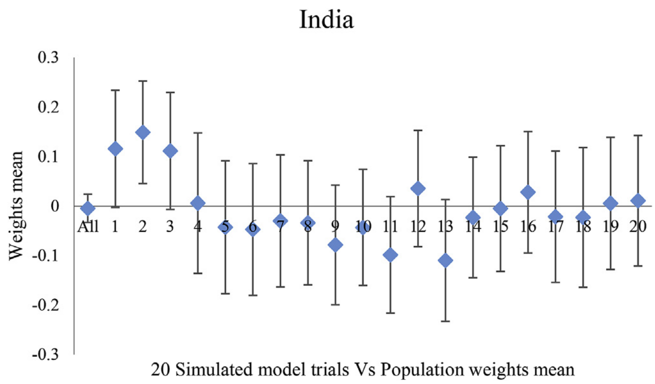

Fig. 3d. Point and interval estimates for 20 trials.

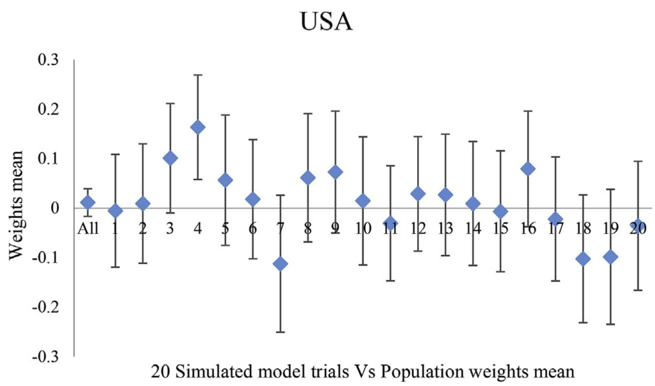

Fig. 3e. Point and interval estimates for 20 trials.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_a - y_p\right)^2}{\sum_{i=1}^{n}(y_a - \bar{y})^2} \tag{15}$$

Where $\bar{y}$ is the mean of the CO_2 intensities. R^2 for each trial in each country is presented in Appendix Table Ia - Ie. After 20 simulated model trials for each country, the CIs are presented in Fig. 3a–e. For Australia, except the 10th and 16th runs, the remaining runs contain the population weights mean (see Fig. 3a) while for Brazil, except the 3rd and 4th runs, the remaining runs contain the population weights mean (see Fig. 3b). For China, except the 1st, 13th, and 19th runs, the remaining runs contain the population weights mean (see Fig. 3c). For India, except the 1st, 2nd, 3rd, and 13th runs, the remaining runs contain the population weights mean (see Fig. 3d). Lastly, for USA, except the 3rd and 4th runs, the remaining runs contain the population weights mean (see Fig. 3e). By eliminating the runs that could not contain the population weights mean, random effects are avoided to ensure reproducibility of results.

The CO_2 intensities resulted from the various iterations for each country is denormalized to obtain the original and predicted CO_2 intensities. Denormalisation is computed using Eq. (16);

$$y = y_{norm}(\max(y) - \min(y)) + \min(y) \tag{16}$$

Further, for all countries mean absolute deviations (MADs) were computed after denormalisation. Trials with negligible/low MSEs and MADs were selected for further evaluation. The MADs are presented in Appendix Table Ia - Ie. The MADs for Australia ranges between 0.01054 and 0.01649; 0.01227 to 0.02305 for Brazil; 0.01536 to 0.03093 for China; 0.00919 to 0.03652 for India and 0.00458 to 0.03976 for USA. The MADs are determined using Eq. (17):

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|y_a - y_p\right| \tag{17}$$

The optimal models for each country were finally selected based on the run with the sample weight mean closer to the population weights mean with negligible MAD and MSE. Using this criteria, the 18th run for Australia (SE = 0.05641, MAD = 0.01193, MSE_{train} = 0.01090, MSE_{test} = 0.01020), the 11th run for Brazil (SE = 0.06544, MAD = 0.01345, MSE_{train} = 0.00570, MSE_{test} = 0.00420), the 11th run for China (SE = 0.06433, MAD = 0.01536, MSE_{train} = 0.00330, MSE_{test} = 0.00330), the 15th run for India (SE = 0.06480, MAD = 0.00919, MSE_{train} = 0.00045, MSE_{test} = 0.00042), and the 6th run for USA (SE = 0.06124, MAD = 0.00458, MSE_{train} = 0.00440, MSE_{test} = 0.00530) were selected (see Appendix Table Ia – Ie). This indicates how precise and close the weight points tend to approach/converge at the true population weights mean with the given data (Boateng et al., 2019). Table 3 presents the selected models and their confidence limits.

The R^2 for each selected model in individual countries are shown in Fig. 4a–e. Australia, Brazil, China, India, and USA achieved coefficients of 0.8011, 0.9139, 0.9521, 0.9944, and 0.8721 respectively. The high R^2 values indicate how well the 9-5-1 MLP with BP models fit the data. Therefore, there are strong relationships between the developed models and the output variables for each country.

The MSE values on both the training and test sets are illustrated in Fig. 5. The MSE values for each case are approximately Zero (0). This affirms that the developed models are sufficient to perform the necessary computations with minimal or negligible forecasting error.

4.2. Validation of the ANN models

With 29 test samples, the 9-5-1 MLPs were employed to predict the CO_2 emission intensities from the 9 input parameters. Absolute deviations (ADs) were computed to validate the models. The AD is equal to the positive proportion of the difference between the actual (y_a) and predicted (y_p) observations to the actual observation (y_a) of the model (Patel and Jha, 2016). AD for Australia ranged from 0.000128408 to 0.037267504, 0.000544838 to 0.039480646 for Brazil, 0.000551518 to 0.047491399 for China, 0.000404588 to 0.028095168 for India, and 0.00024287 to 0.03549516 for USA (see Appendix Table IIa – IIc). The range of ADs shows that the trained model is capable of forecasting the intensity of CO_2 emissions for each country. Fig. 6a–e shows the actual CO_2 emission intensities versus the predicted CO_2 emission intensities from the 29 test samples (quarters) for each country.

5. Closed-form formula for predicting CO_2 emission intensity

For the purpose of environmental policymakers and consultants, a simplified closed-form Eqs. (18) and (19) can be used for predicting the intensity of CO_2 emission. The closed-form equations need the values of the inputs, weights of the links between the neurons in different layers, and the biases of the output and input neurons (Patel and Jha, 2015; Tadesse et al., 2012). The closed-form formula presented in this study is suitable for use where the activation function for the output layer is the sigmoid function. The output O_1 from Fig. 2 can be obtained from computing Eqs. (18) and (19). Where Eq. (18) is the formula for predicting the output (carbon emission intensity).

Table 3
Selected models and their confidence limits on extracted weights.

Country	Run	Lower limit*	Upper limit*	Mean	P_{mean}
Australia	18th	−0.124120166	0.097003346	−0.01355841	−0.029038403
Brazil	11th	−0.114179821	0.142364429	0.014092304	−0.006875717
China	11th	−0.132262709	0.119915949	−0.00617338	−0.007379938
India	15th	−0.132083021	0.121917025	−0.005082998	−0.004772717
USA	6th	−0.101997647	0.138054655	0.018028504	0.011375343

*95% confidence interval, P_{mean} = population mean.

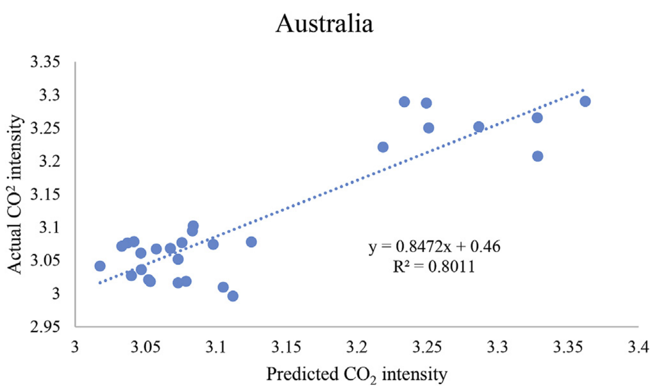

Fig. 4a. Scatter chart of actual and predicted CO_2 intensities.

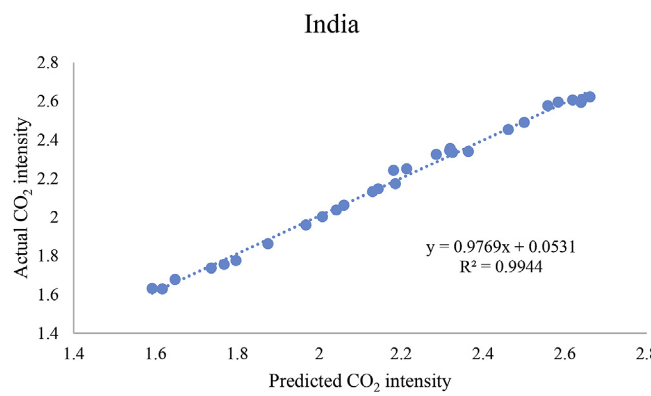

Fig. 4d. Scatter chart of actual and predicted CO_2 intensities.

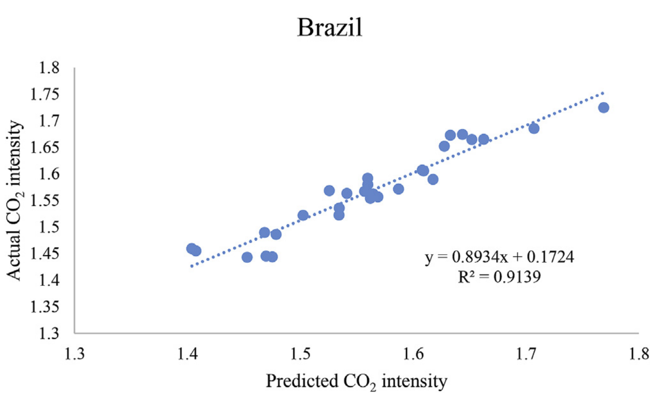

Fig. 4b. Scatter chart of actual and predicted CO_2 intensities.

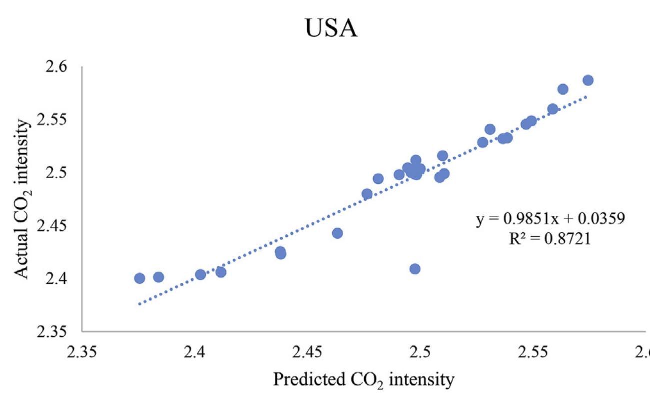

Fig. 4e. Scatter chart of actual and predicted CO_2 intensities.

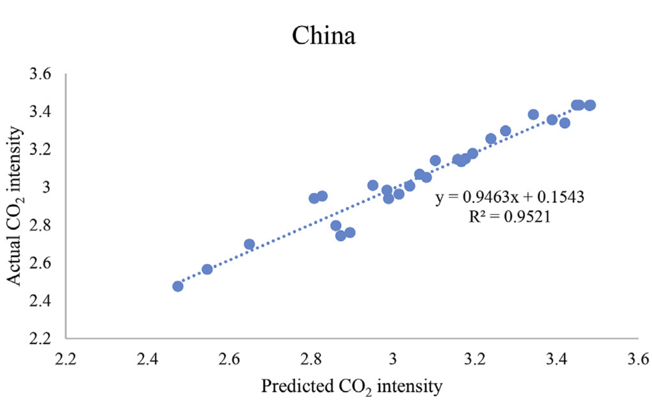

Fig. 4c. Scatter chart of actual and predicted CO_2 intensities.

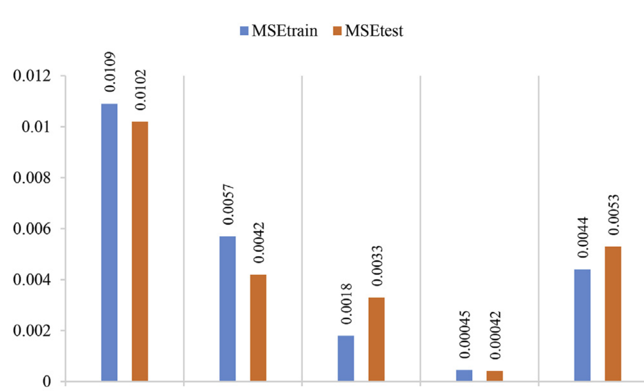

Fig. 5. Regression metric scores.

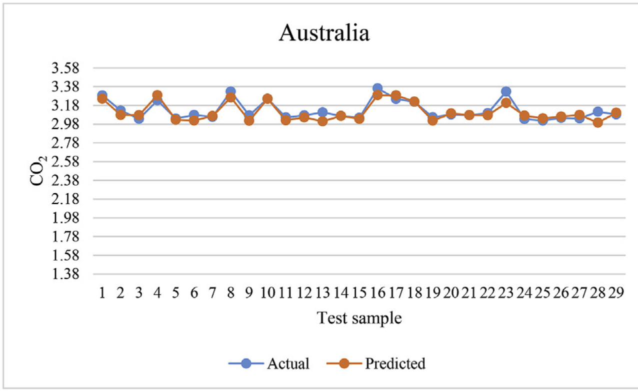

Fig. 6a. Actual versus predicted CO_2 intensities.

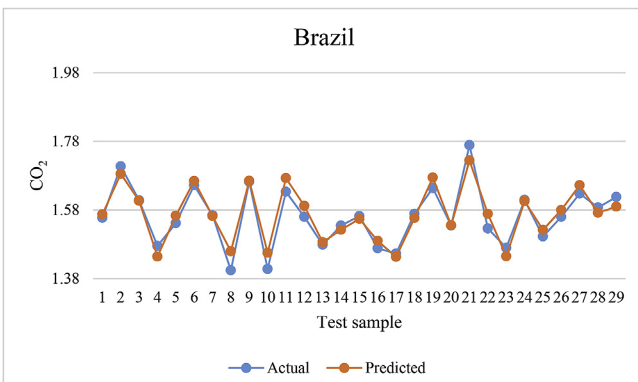

Fig. 6b. Actual versus predicted CO_2 intensities.

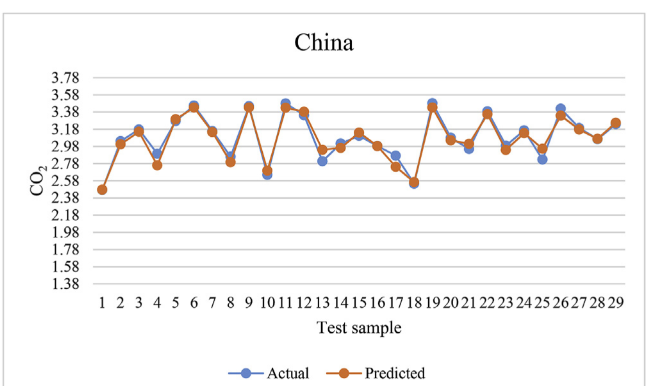

Fig. 6c. Actual versus predicted CO_2 intensities.

$$O_1 = \frac{1}{1 + e^{-\left(bias_o + \sum_{k=1}^{r} \frac{w^{ho}_{k,1}}{1+e^{-H_k}}\right)}} \tag{18}$$

Where r is the number of hidden neurons respectively; $bias_o$ is the bias of the output layer neuron; $w^{ho}_{k,1}$ is the weight of the link between H_k and O_1. Eq. (19) is used for calculating the *kth* hidden layer neuron.

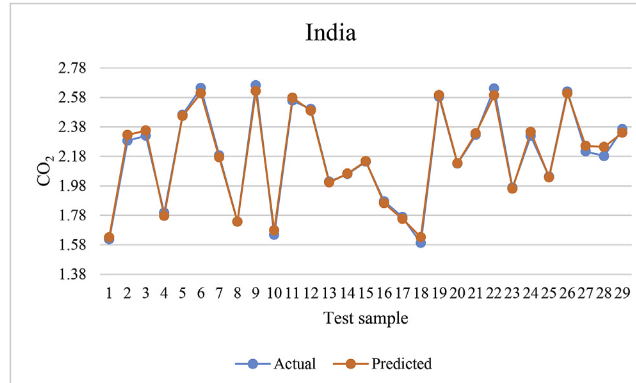

Fig. 6d. Actual versus predicted CO_2 intensities.

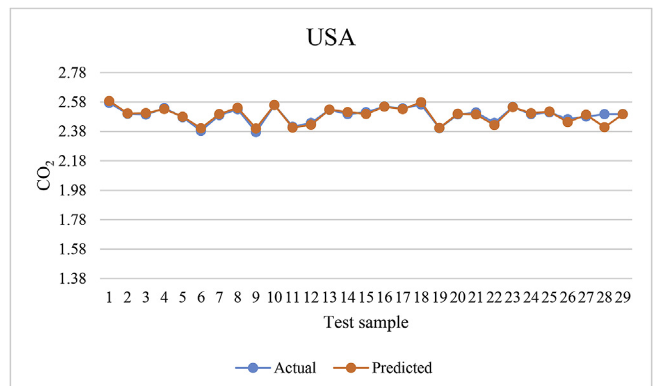

Fig. 6e. Actual versus predicted CO_2 intensities.

$$H_k = \sum_{j=1}^{q} w^{ih}_{j,k} \times I_j + bias_k \tag{19}$$

Where q is the number of the input parameters; $bias_k$ is the bias of the *kth* hidden layer neuron (H_k); $w^{ih}_{j,k}$ the weight of the link between I_j and H_k. For each country, the weights and biases are presented in Tables 4a–4e.

The closed-form expression can be used to predict CO_2 emission intensity based on the previous input values. An illustrative example is demonstrated afterwards.

5.1. Illustrative example

For practical purpose, we demonstrate how to use the above closed-form formula for predicting/forecasting carbon emission intensity[3]. Using India as an illustration, consider the nine input parameters (I_1 to I_9) for determining the CO_2 emission intensity for 2011Q4 (Table 5). The CO_2 emission intensity for the next quarter (2012Q1) O_1 may be obtained by the following steps:

The values of H_1 to H_5 are obtained as −2.047745743, 2.05904476, −1.236657889, −0.972341664, and 0.012887535, respectively.

[3] Following the steps used for the illustration, one can predict for the remaining countries (Australia, Brazil, China and the USA) by substituting the weights, biases and values of the input variables for respective countries into the closed-form formula.

Table 4a
Weight values and biases for neural network (Australia).

Link	Weight/bias	Number of hidden layer neuron (k)				
		1	2	3	4	5
Input to hidden layer	$w_{1,k}^{ih}$	0.480	−0.677	−0.371	0.582	−0.750
	$w_{2,k}^{ih}$	−0.026	0.326	0.018	−0.312	−0.252
	$w_{3,k}^{ih}$	−0.216	0.228	0.126	−0.265	0.180
	$w_{4,k}^{ih}$	−0.183	0.529	−0.179	−0.385	0.457
	$w_{5,k}^{ih}$	0.262	0.220	−0.314	0.401	−0.089
	$w_{6,k}^{ih}$	−0.500	0.486	−0.419	−0.229	0.532
	$w_{7,k}^{ih}$	−0.304	0.597	−0.397	0.190	−0.088
	$w_{8,k}^{ih}$	0.039	0.171	−0.210	0.527	−0.194
	$w_{9,k}^{ih}$	0.029	−0.347	−0.225	0.314	−0.619
	$bias_k$	−0.036	0.298	0.002	−0.195	0.022
Hidden layer to output	$w_{k,1}^{ho}$	−0.971	−0.363	0.452	0.276	0.786
	$bias_o$	−0.161				

Table 4b
Weight values and biases for neural network (Brazil).

Link	Weight/bias	Number of hidden layer neuron (k)				
		1	2	3	4	5
Input to hidden layer	$w_{1,k}^{ih}$	0.237	0.538	−0.358	−0.035	0.549
	$w_{2,k}^{ih}$	−0.459	−0.651	0.299	−0.376	0.210
	$w_{3,k}^{ih}$	−0.330	0.848	0.196	−0.739	−0.592
	$w_{4,k}^{ih}$	0.197	0.074	−0.873	0.250	−0.022
	$w_{5,k}^{ih}$	0.208	0.067	−0.346	0.650	−0.307
	$w_{6,k}^{ih}$	0.046	0.313	0.165	−0.303	−0.557
	$w_{7,k}^{ih}$	0.033	−0.466	0.181	−0.338	−0.505
	$w_{8,k}^{ih}$	0.178	0.238	−0.234	0.033	−0.254
	$w_{9,k}^{ih}$	0.538	−0.315	0.054	0.030	−0.145
	$bias_k$	−0.352	0.032	0.268	0.070	0.024
Hidden layer to output	$w_{k,1}^{ho}$	1.062	1.148	1.091	−0.552	0.028
	$bias_o$	−0.236				

Table 4c
Weight values and biases for neural network (China).

Link	Weight/bias	Number of hidden layer neuron (k)				
		1	2	3	4	5
Input to hidden layer	$w_{1,k}^{ih}$	0.240	−0.147	−0.552	0.645	0.384
	$w_{2,k}^{ih}$	0.265	−0.026	0.316	0.491	0.498
	$w_{3,k}^{ih}$	0.299	−0.266	−0.657	−0.462	−0.549
	$w_{4,k}^{ih}$	0.349	−0.484	−0.777	−0.649	0.522
	$w_{5,k}^{ih}$	0.847	0.285	−0.183	0.724	0.196
	$w_{6,k}^{ih}$	0.294	0.359	0.501	−0.101	0.200
	$w_{7,k}^{ih}$	0.128	−0.636	0.177	−0.348	−0.403
	$w_{8,k}^{ih}$	−0.172	−0.959	0.373	0.505	−0.301
	$w_{9,k}^{ih}$	−0.167	−0.751	−0.273	−0.383	0.507
	$bias_k$	0.158	−0.222	0.097	−0.324	−0.190
Hidden layer to output	$w_{k,1}^{ho}$	1.064	−0.727	0.867	−0.484	0.190
	$bias_o$	0.044				

Table 4d
Weight values and biases for neural network (India).

Link	Weight/bias	Number of hidden layer neuron (k)				
		1	2	3	4	5
Input to hidden layer	$w^{ih}_{1,k}$	−0.497	0.383	−0.468	0.626	−0.253
	$w^{ih}_{2,k}$	−0.508	0.130	0.180	−0.467	0.775
	$w^{ih}_{3,k}$	0.237	0.063	0.794	0.218	0.410
	$w^{ih}_{4,k}$	0.132	0.460	0.011	0.234	−0.154
	$w^{ih}_{5,k}$	−0.264	0.359	−0.503	−0.316	0.355
	$w^{ih}_{6,k}$	0.016	0.284	0.228	−0.541	−0.139
	$w^{ih}_{7,k}$	−0.326	0.229	−0.919	−0.329	0.240
	$w^{ih}_{8,k}$	0.344	−0.142	−0.167	0.238	−0.709
	$w^{ih}_{9,k}$	−0.772	−0.250	0.061	0.381	−0.125
	$bias_k$	−0.169	0.134	−0.307	0.267	0.427
Hidden layer to output	$w^{ho}_{k,1}$	−1.091	0.149	−0.490	1.296	0.342
	$bias_o$	0.122				

Table 4e
Weight values and biases for neural network (USA).

Link	Weight/bias	Number of hidden layer neuron (k)				
		1	2	3	4	5
Input to hidden layer	$w^{ih}_{1,k}$	0.299	0.671	−0.756	0.075	−0.057
	$w^{ih}_{2,k}$	−0.168	−0.370	−0.374	−0.255	0.183
	$w^{ih}_{3,k}$	−0.107	−0.646	−0.148	0.657	0.563
	$w^{ih}_{4,k}$	−0.436	−0.319	0.305	−0.864	−0.037
	$w^{ih}_{5,k}$	0.348	0.161	−0.263	−0.547	−0.244
	$w^{ih}_{6,k}$	−0.155	0.461	−0.231	−0.066	−0.098
	$w^{ih}_{7,k}$	−0.548	0.712	0.486	−0.585	0.253
	$w^{ih}_{8,k}$	0.574	−0.587	0.211	−0.080	−0.238
	$w^{ih}_{9,k}$	0.189	0.582	0.709	−0.060	−0.034
	$bias_k$	−0.036	0.298	0.002	−0.195	0.022
Hidden layer to output	$w^{ho}_{k,1}$	−0.427	0.359	−0.004	−0.380	−0.214
	$bias_o$	−0.305				

Table 5
Input values and the output value for 2011Q4, India.
Step 1 Insert the standardised values of the input parameters (Table 5) and weights and biases of input to the hidden layer (Table 4d) in Eq. (19) to compute H_1 to H_5 as given in Eq. 20–24.

$$H1 = (-0.497I1 - 0.508I2 - 0.237I3 + 0.132I4 - 0.264I5 + 0.016I6 - 0.326I7 + 0.344I8 - 0.772I9) - 0.169 \quad (20)$$

$$H2 = (0.383I1 + 0.130I2 + 0.063I3 + 0.460I4 + 0.359I5 + 0.284I6 + 0.229I7 - 0.142I8 - 0.250I9) + 0.134 \quad (21)$$

$$H3 = (-0.468I1 + 0.180I2 + 0.794I3 + 0.011I4 - 0.503I5 + 0.228I6 - 0.919I7 - 0.167I8 + 0.061I9) - 0.307 \quad (22)$$

$$H4 = (0.626I1 - 0.467I2 + 0.218I3 + 0.234I4 - 0.316I5 - 0.541I6 - 0.329I7 + 0.238I8 + 0.381I9) + 0.267 \quad (23)$$

$$H5 = (-0.253I1 + 0.775I2 + 0.410I3 - 0.154I4 + 0.355I5 - 0.139I6 + 0.240I7 - 0.709I8 - 0.125I9) + 0.427 \quad (24)$$

Period	2011Q4 (destandardised)	2011Q4 (standardised)
Energy consumption (I_1)	586.5490144	1.797073524
Financial development (I_2)	0.405568259	0.847736897
Economic growth (I_3)	1.905736931	1.583596755
Foreign direct investment (I_4)	1440.250772	1.172634771
Industrialisation (I_5)	30.00708424	0.921162953
Technology (I_6)	198210.5313	1.662170004
Population (I_7)	1253238699	1.307734943
Trade openness (I_8)	56.58837488	1.861353516
Urbanisation (I_9)	393609283.8	1.402126680
CO_2 emission intensity (O)	2.583927266	0.843589044*
CO_2 emission intensity for 2012Q1	y_p	O_1?

Note: *normalised, destandardisation: $x = (x_{stand} \times \sigma) + .\mu$

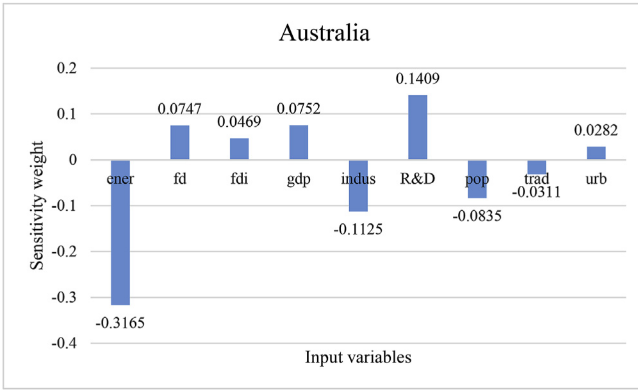

Fig. 7a. Sensitivity analysis of CO_2 emission intensity determinants.

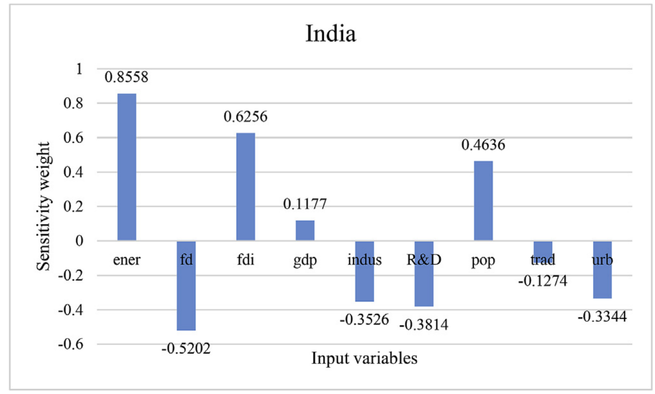

Fig. 7d. Sensitivity analysis of CO_2 emission intensity determinants.

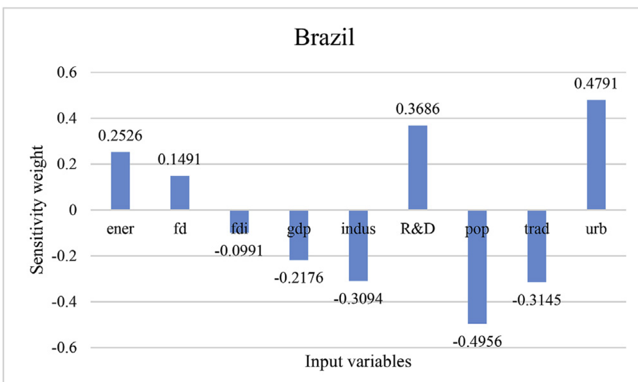

Fig. 7b. Sensitivity analysis of CO_2 emission intensity determinants.

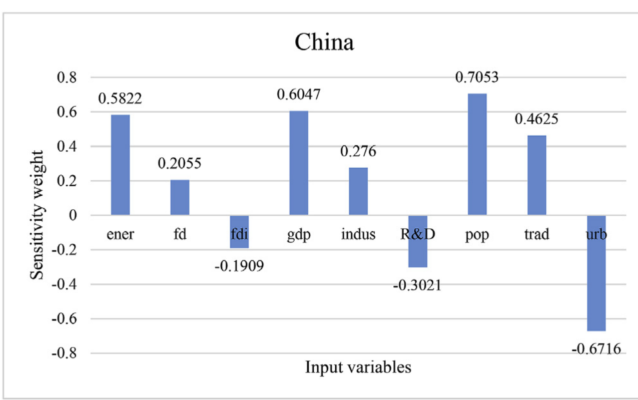

Fig. 7c. Sensitivity analysis of CO_2 emission intensity determinants.

Step 2 Insert the values of H_1 to H_5 and the weights and biases of the hidden to output layer (Table 4d) in Eq. (18) as given in Eq. (25). The value of the predicted output O_1 is 0.756145926.

$$O_1 = \frac{1}{1 + e^{-\left(0.122 - \frac{1.091}{1+e^{-H_1}} + \frac{0.149}{1+e^{-H_2}} - \frac{0.490}{1+e^{-H_3}} + \frac{1.296}{1+e^{-H_4}} + \frac{0.342}{1+e^{-H_5}}\right)}} \tag{25}$$

Step 3 The value obtained from Eq. (25) is the normalised value (y_{norm}). Eq. (16) is used to denormalize O_1 as given in Eq. (26):

$$y_p = 0.756145926(2.777034539 - 1.542419792) + 1.542419792 \tag{26}$$

The actual CO_2 intensity (y_a) for 2012Q1 is 2.6430 and the predicted CO_2 intensity (y_p) for 2012Q1 is 2.4760. The AD for this forecast is 0.0632.

6. Sensitivity analysis

Sensitivity analysis is conducted to identify the extent to which each input variable contributes to the intensity of carbon emissions in Australia, Brazil, China, India, and the USA. To conduct the sensitivity analysis, the Partial Rank Correlation Coefficient (PRCC) between carbon emission intensity and each input variable is calculated for each country. Fig. 7a–d depicts the normalised sensitivity weight of each input variable for each country. Fig. 7a shows that in Australia, R&D has the highest sensitivity weight, followed by economic growth, financial development, foreign direct investment and urbanisation. As depicted in Fig. 7a, the PRCC results show that R&D (0.1409), economic growth (0.0752), financial development (0.0747), foreign direct investment (0.0469) and urbanisation (0.0282) increase carbon emissions intensity while energy consumption (−0.3165), industrialisation (−0.1125), population (−0.0835) and trade openness (−0.0311) reduce carbon emission intensity in Australia.

Fig. 7b indicates that in Brazil, urbanisation has the highest sensitivity weight followed by R&D, energy consumption and financial development. PRCC results show that in Brazil (see Fig. 7b), urbanisation (0.4791), R&D (0.3686), energy consumption (0.2526) and financial development (0.1491) increases carbon emissions intensity while population (−0.4956), trade openness (−0.3145), industrialisation (−0.3094), economic growth (−0.2176), population (−0.0835) and foreign direct investment (−0.0991) contribute to reduction in carbon emission intensity.

In China, as depicted Fig. 7c, population size has the highest sensitivity weight followed by economic growth, energy consumption, trade openness, industrialisation, and financial development. The PRCC results as shown in Fig. 7c shows that population (0.7053), economic growth (0.6047), energy consumption (0.5822), trade openness (0.4625), industrialisation (0.276) and financial development (0.2055) are the forces behind carbon emissions in China while urbanisation (−0.6716), R&D (−0.3021) and foreign direct investment (−0.3094) reduce the intensity of carbon emissions.

For India, Fig. 7d shows that energy consumption has the highest sensitivity weight followed by foreign direct investment, population, and economic growth. As depicted in Fig. 7d, the factors

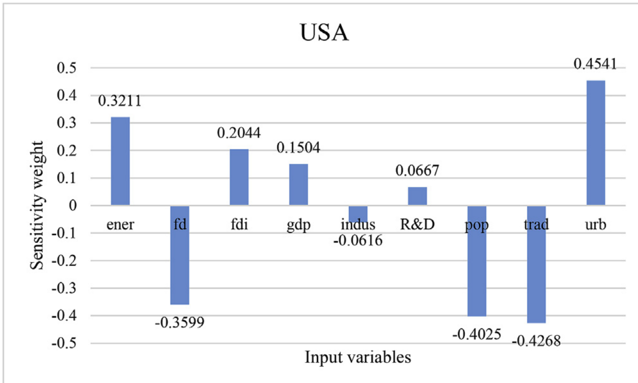

Fig. 7e. Sensitivity analysis of CO_2 emission intensity determinants.

responsible for the growth of carbon emission intensity include energy consumption (0.8558), foreign direct investment (0.6256), population (0.4636) and economic growth (0.1177) while financial development (−0.5202), R&D (−0.3814), industrialisation (−0.3526), urbanisation (−0.334) and trade openness (−0.1274) contribute to the reduction in carbon emission intensity.

For USA, urbanisation has the highest sensitivity weight, followed by foreign direct investment, economic growth and R&D (see Fig. 7e). Fig. 7e shows that the factors contributing to the rise of carbon emission intensity in USA include urbanisation (0.4541) energy consumption (0.3211), foreign direct investment (0.2044), economic growth (0.1504) and R&D (0.0667) while trade openness (−0.4261), population (−0.4025), financial development (−0.3599) and industrialisation (−0.0616) reduces carbon emission intensity.

The results from the sensitivity analysis revealed that each of the input has an important but different influence on the intensity of carbon emissions of the countries considered. Therefore, carbon emissions models that tend to ignore these variables could result in the underestimation of the actual carbon emission intensity.

7. Conclusion and policy implications

The applicability of the artificial neural network (ANN) technique for predicting CO_2 emission intensity was evaluated for Australia, Brazil, China, India, and USA. The type of neural network used for each country was the feed forward multi-layer perceptron (FFMLP). A stochastic gradient descent with the backpropagation algorithm was employed to train the networks over several iterations. The 9-5-1 FFMLPs take into account energy consumption, financial development, foreign direct investment, economic growth, industrialisation, technology, population, trade openness, and urbanisation scores of the selected countries. Five ANN models were developed with 115 quarters and validated on 29 quarters for the prediction of CO_2 emission intensity for the five countries. The results of this study are very promising and showed good generalization. The predicted versus actual values indicate negligible or approximately zero errors for the AD, MAD, MSE, SD, SE, and ME along with higher coefficients of determination (R^2) of 0.80 for Australia, 0.91 for Brazil, 0.95 for China, 0.99 for India, and 0.87 for USA. This study does not only proposes a novel ANN technique for predicting CO_2 emission intensity but also presents a closed-form solution for predicting CO_2 emission intensity for Australia, Brazil, China, India, and USA with insignificant forecasting deviations. Software developers could also use the closed-form solution, the model architecture, and the extracted weights and biases of each parameter to develop a CO_2 emission intensity application on various platforms for the five countries using any programming language.

As a machine learning (ML) technique, the developed ANN models overcome the limitations of statistical approaches and are very practical to use. Due to the stochastic nature of neural networks, this study further proposes a robust methodology in selecting an optimal model for stable reproducibility of results. The ANN models presented in this study have been validated and reliable to predict the growth of CO_2 emission intensity for Australia, Brazil, China, India, and USA with negligible forecasting errors. Additionally, the results from the sensitivity analysis revealed that for Australia, R&D has the highest sensitivity weight while for Brazil and the USA, urbanisation has the highest sensitivity weight. For China, population size has the highest sensitivity weight while energy consumption has the highest sensitivity weight in India. The implication from the sensitivity results is that environmental policymakers in each respective country should prioritise these variables when designing and implementing environmental (climate change) policies. Additionally, the models developed from this study could serve as tools for international organisations and environmental policymakers to design and implement environmental policies and strategies to monitor and control environmental problems.

Future studies could consider performance evaluation of ANN models for prediction of CO_2 emission intensity with other ML approaches such as support vector regression (SVR) and recurrent neural network (RNN). This sort of evaluation would offer a dais for the methodological rigour in the selection of other ML tools that may give predictions that are more accurate. Other high CO_2 emitting countries such as Russia, Japan, and Germany could adopt the flow process of this study's methodology to develop robust predictive ANN models for guiding decision making when drafting environmental (climate change) policies.

Acknowledgements

The authors wish to deeply thank the Editorial Board of the journal for their time and support. We are also thankful to the two anonymous reviewers for their valuable comments that help us to improve the quality of this paper. Nevertheless, the authors are only responsible for all remaining errors or imperfections.

Appendix

Appendix Ia
Comparison of selected optimal model and other ANN models (Australia).

Model	R^2	MSE_{train}	MSE_{test}	SD	SE	MAD	ME_y
1	0.75280	0.01290	0.01290	0.42690	0.06037	0.01410	0.02076
2	0.64220	0.01180	0.01830	0.42849	0.06060	0.01646	0.01560
3	0.76190	0.01240	0.01260	0.43203	0.06110	0.01410	0.02152
4	0.82680	0.01180	0.00830	0.41794	0.05910	0.01054	0.01273
5	0.79290	0.01140	0.00930	0.43954	0.06216	0.01112	0.00656
6	0.74940	0.01120	0.01430	0.41651	0.05890	0.01456	0.02506
7	0.68230	0.01310	0.01470	0.40492	0.05726	0.01447	0.01224
8	0.80390	0.00750	0.01080	0.43129	0.06099	0.01235	0.02030
9	0.75600	0.01190	0.01360	0.39712	0.05616	0.01322	0.02507
10	0.69430	0.01390	0.01840	0.41533	0.05874	0.01649	0.03371
11	0.67830	0.01180	0.01580	0.40661	0.05750	0.01509	0.01525
12	0.74020	0.01320	0.01180	0.38728	0.05477	0.01280	0.00765
13	0.78040	0.01150	0.01080	0.41848	0.05918	0.01265	0.01598
14	0.64300	0.01040	0.01740	0.41846	0.05918	0.01573	0.01162
15	0.78840	0.01070	0.01020	0.41634	0.05888	0.01234	0.01297
16	0.70310	0.00880	0.01380	0.45046	0.06370	0.01378	0.00786
17	0.76070	0.00910	0.01110	0.44654	0.06315	0.01210	0.01064
18	**0.80110**	**0.01090**	**0.01020**	**0.39887**	**0.05641**	**0.01193**	**0.01778**
19	0.71020	0.01320	0.01310	0.38845	0.05494	0.01276	0.00600
20	0.77700	0.01290	0.01050	0.38632	0.05463	0.01224	0.01251

Note: MSE = mean square error, SD = standard deviation, SE = standard error, MAD = mean absolute deviation, ME_y = mean error on prediction.

Appendix Ib
Comparison of selected optimal model and other ANN models (Brazil).

Model	R^2	MSE_{train}	MSE_{test}	SD	SE	MAD	ME_y
1	0.89430	0.00650	0.00540	0.48114	0.06804	0.01479	−0.00897
2	0.88680	0.00740	0.00650	0.48239	0.06822	0.01622	−0.01403
3	0.70370	0.01800	0.01450	0.37132	0.05251	0.02305	−0.01125
4	0.87870	0.00690	0.00610	0.51981	0.07351	0.01589	−0.00825
5	0.81460	0.00880	0.00900	0.50558	0.07150	0.02011	−0.00877
6	0.75540	0.01580	0.01250	0.47784	0.06758	0.02040	−0.01319
7	0.81900	0.01230	0.00860	0.47053	0.06654	0.01820	−0.00641
8	0.88110	0.00540	0.00620	0.50556	0.07150	0.01600	−0.00920
9	0.91020	0.00480	0.00420	0.48854	0.06909	0.01227	−0.00312
10	0.89100	0.00650	0.00610	0.48999	0.06929	0.01591	−0.01232
11	**0.91390**	**0.00570**	**0.00420**	**0.46277**	**0.06544**	**0.01345**	**−0.00597**
12	0.79740	0.01240	0.01050	0.49058	0.06938	0.02174	−0.01332
13	0.88450	0.00740	0.00640	0.47772	0.06756	0.01633	−0.01286
14	0.80050	0.01290	0.00980	0.45652	0.06456	0.01977	−0.01001
15	0.90760	0.00550	0.00500	0.46081	0.06517	0.01460	−0.01031
16	0.74890	0.01450	0.01290	0.44537	0.06298	0.02216	−0.01377
17	0.87870	0.00700	0.00650	0.46594	0.06589	0.01613	−0.01168
18	0.85470	0.00890	0.00730	0.50782	0.07182	0.01763	−0.00943
19	0.84500	0.01160	0.00770	0.50151	0.07092	0.01719	−0.00882
20	0.86580	0.00800	0.00700	0.44253	0.06258	0.01736	−0.01128

Note: MSE = mean square error, SD = standard deviation, SE = standard error, MAD = mean absolute deviation, ME_y = mean error on prediction.

Appendix Ic
Comparison of selected optimal model and other ANN models (China).

Model	R^2	MSE_{train}	MSE_{test}	SD	SE	MAD	ME_y
1	0.90790	0.00490	0.00650	0.43691	0.06179	0.02537	0.02060
2	0.93890	0.00370	0.00400	0.44958	0.06358	0.01795	0.00483
3	0.92060	0.00480	0.00560	0.40740	0.05762	0.02277	0.01653
4	0.93380	0.00310	0.00450	0.48241	0.06822	0.01990	0.01332
5	0.84030	0.00900	0.01420	0.49285	0.06970	0.03087	0.05190
6	0.83180	0.01430	0.01170	0.45484	0.06432	0.02740	−0.01303
7	0.92000	0.00350	0.00530	0.47023	0.06650	0.02045	0.00511
8	0.95550	0.00230	0.00320	0.44949	0.06357	0.01794	0.01729
9	0.91480	0.00380	0.00560	0.44856	0.06344	0.02265	0.00120
10	0.91250	0.00290	0.00580	0.49364	0.06981	0.02065	0.01016
11	**0.95210**	**0.00180**	**0.00330**	**0.45489**	**0.06433**	**0.01536**	**0.01128**
12	0.92050	0.00360	0.00530	0.43513	0.06154	0.02127	0.01063
13	0.94290	0.00300	0.00390	0.45553	0.06442	0.01840	0.01299
14	0.93830	0.00340	0.00430	0.45426	0.06424	0.01920	0.01384
15	0.92940	0.00330	0.00470	0.44908	0.06351	0.01993	0.00545
16	0.92370	0.00290	0.00510	0.46805	0.06619	0.02045	0.00669
17	0.92870	0.00350	0.00480	0.42924	0.06070	0.01980	0.01139
18	0.93450	0.00410	0.00460	0.41507	0.05870	0.02044	0.01741
19	0.83630	0.01030	0.01480	0.37316	0.05277	0.03093	0.05035
20	0.93890	0.00240	0.00420	0.41736	0.05902	0.01935	0.01190

Note: MSE = mean square error, SD = standard deviation, SE = standard error, MAD = mean absolute deviation, ME_y = mean error on prediction.

Appendix Id
Comparison of selected optimal model and other ANN models (India).

Models	R^2	MSE_{train}	MSE_{test}	SD	SE	MAD	ME_y
1	0.96870	0.00500	0.00360	0.42662	0.06033	0.02529	−0.02168
2	0.93530	0.00820	0.00640	0.37290	0.05274	0.03652	−0.03435
3	0.93600	0.00730	0.00590	0.42554	0.06018	0.03484	−0.02437
4	0.98260	0.00140	0.00140	0.51222	0.07244	0.01750	0.00730
5	0.98460	0.00140	0.00110	0.48376	0.06841	0.01670	0.00599
6	0.98250	0.00093	0.00130	0.47938	0.06779	0.01500	−0.00433

Appendix Id (*continued*)

Models	R^2	MSE_{train}	MSE_{test}	SD	SE	MAD	ME_y
7	0.98680	0.00086	0.00099	0.48183	0.06814	0.01510	0.00561
8	0.96480	0.00210	0.00260	0.45240	0.06398	0.01906	−0.01174
9	0.95520	0.00260	0.00320	0.43564	0.06161	0.02040	0.00338
10	0.93130	0.00420	0.00480	0.42340	0.05988	0.02908	−0.00064
11	0.97320	0.00170	0.00190	0.42415	0.05998	0.02126	0.00353
12	0.94780	0.00290	0.00370	0.42418	0.05999	0.02982	−0.00639
13	0.98740	0.00088	0.00093	0.44412	0.06281	0.01388	−0.00667
14	0.96830	0.00200	0.00220	0.43985	0.06220	0.02085	0.00087
15	**0.99440**	**0.00045**	**0.00042**	**0.45818**	**0.06480**	**0.00919**	**−0.00280**
16	0.99060	0.00069	0.00068	0.44326	0.06269	0.01164	−0.00406
17	0.98220	0.00160	0.00130	0.47885	0.06772	0.01675	0.00521
18	0.96940	0.00200	0.00220	0.50918	0.07201	0.02186	−0.00113
19	0.98490	0.00120	0.00120	0.48186	0.06815	0.01722	0.00927
20	0.95850	0.00250	0.00290	0.47591	0.06730	0.02446	0.00143

Note: MSE = mean square error, SD = standard deviation, SE = standard error, MAD = mean absolute deviation, ME_y = mean error on prediction.

Appendix Ie
Comparison of selected optimal model and other ANN models (USA).

Model	R^2	MSE_{train}	MSE_{test}	SD	SE	MAD	ME_y
1	0.84680	0.00550	0.00690	0.41045	0.05805	0.00533	−0.00062
2	0.81800	0.00810	0.00720	0.43459	0.06146	0.00564	−0.00472
3	0.87480	0.00420	0.00580	0.39801	0.05629	0.00537	0.00254
4	0.85110	0.00480	0.00650	0.38049	0.05381	0.00567	0.00141
5	0.88900	0.00370	0.00530	0.47439	0.06709	0.00499	0.00169
6	**0.87210**	**0.00440**	**0.00530**	**0.43302**	**0.06124**	**0.00458**	**0.00118**
7	0.89690	0.00280	0.00550	0.49859	0.07051	0.00486	0.00291
8	0.87300	0.00410	0.00560	0.46706	0.06605	0.00521	0.00124
9	0.86730	0.00610	0.00550	0.44389	0.06278	0.00512	−0.00027
10	0.86030	0.00340	0.00730	0.46693	0.06603	0.00636	0.00096
11	0.89030	0.00300	0.00540	0.41896	0.05925	0.00466	0.00251
12	0.84240	0.00540	0.00630	0.41731	0.05902	0.00532	−0.00034
13	0.83300	0.00800	0.00680	0.44197	0.06250	0.00518	−0.00490
14	0.88570	0.00280	0.00590	0.45145	0.06384	0.00518	0.00326
15	0.88220	0.00480	0.00620	0.44029	0.06227	0.00578	−0.00075
16	0.84810	0.00550	0.00600	0.42097	0.05953	0.00448	−0.00038
17	0.87900	0.00320	0.00620	0.45185	0.06390	0.00479	0.00358
18	0.88500	0.00230	0.00600	−0.10243	0.46541	0.00539	0.00368
19	0.85260	0.00400	0.00690	0.49119	0.06946	0.00544	0.00191
20	0.78400	0.00300	0.00670	0.46985	0.06645	0.03976	−0.00843

Note: MSE = mean square error, SD = standard deviation, SE = standard error, MAD = mean absolute deviation, ME_y = mean error on prediction.

Appendix IIa
Results of evaluating predictions for CO2 emission intensities on selected optimal models.

Test samples	Australia				Brazil			
	y_a	y_p	$AD_{9\text{-}5\text{-}1}$	E_y	y_a	y_p	$AD_{9\text{-}5\text{-}1}$	E_y
1	3.286642486	3.251830856	0.010591852	0.034811631	1.557095671	1.567267068	0.006532288	−0.010171397
2	3.125154889	3.077880797	0.01512696	0.047274092	1.707167999	1.685288219	0.012816418	0.021879779
3	3.037133734	3.076276916	0.012888198	−0.039143182	1.608201304	1.60699964	0.00074721	0.001201664
4	3.233742636	3.289377947	0.017204619	−0.055635311	1.475355053	1.444093351	0.021189274	0.031261702
5	3.039918372	3.026970948	0.004259135	0.012947424	1.541428543	1.563372641	0.014236209	−0.021944098
6	3.078738732	3.018433468	0.019587652	0.060305264	1.652063616	1.664560296	0.007564285	−0.01249668
7	3.057637514	3.067132259	0.003105255	−0.009494745	1.564609994	1.562360404	0.001437796	0.002249591
8	3.328124784	3.26535332	0.01886091	0.062771464	1.404028125	1.459460063	0.039480646	−0.055431938
9	3.073089603	3.016134279	0.018533571	0.056955324	1.662672303	1.665176424	0.001506082	−0.002504121
10	3.251017716	3.249962095	0.000324705	0.001055621	1.407687907	1.455193057	0.033746934	−0.047505151
11	3.052164158	3.02073217	0.010298263	0.031431988	1.633045241	1.672776636	0.024329635	−0.039731395
12	3.073111027	3.051729348	0.006957666	0.021381679	1.559834321	1.591888242	0.020549568	−0.032053922
13	3.1051127	3.009504513	0.030790569	0.095608187	1.478753755	1.486136695	0.004992677	−0.00738294

(*continued on next page*)

Appendix IIa (*continued*)

Test samples	Australia				Brazil			
	y_a	y_p	$AD_{9\text{-}5\text{-}1}$	E_y	y_a	y_p	$AD_{9\text{-}5\text{-}1}$	E_y
14	3.067642054	3.068035964	0.000128408	−0.00039391	1.534474657	1.522429385	0.007849769	0.012045272
15	3.046993661	3.035909155	0.00363785	0.011084506	1.562172938	1.554131514	0.005147589	0.008041424
16	3.362218222	3.290196929	0.021420767	0.072021293	1.468488625	1.489780906	0.014499453	−0.021292282
17	3.249380725	3.287585144	0.011757446	−0.038204419	1.452999157	1.443124254	0.006796221	0.009874903
18	3.218645018	3.221053761	0.000748372	−0.002408744	1.568904846	1.556687011	0.007787492	0.012217834
19	3.053339072	3.018070233	0.011550908	0.035268839	1.643779428	1.674355585	0.018601131	−0.030576157
20	3.083274299	3.094359779	0.00359536	−0.01108548	1.534667613	1.535503758	0.000544838	−0.000836145
21	3.0758051	3.076858286	0.00034241	−0.001053186	1.768920753	1.724573304	0.025070342	0.044347448
22	3.097988232	3.074213878	0.007674127	0.023774355	1.525899465	1.568506383	0.027922494	−0.042606918
23	3.328440301	3.207311214	0.036392147	0.121129088	1.469795395	1.445266386	0.016688724	0.02452901
24	3.033172721	3.071346465	0.012585417	−0.038173744	1.60941944	1.605598744	0.002373959	0.003820696
25	3.017621789	3.041308013	0.007849302	−0.023686224	1.502641929	1.522103477	0.012951554	−0.019461548
26	3.046647468	3.0608779	0.004670849	−0.014230432	1.559945702	1.579782966	0.012716637	−0.019837264
27	3.0417623	3.07815298	0.011963683	−0.03639068	1.627733054	1.652092246	0.014965103	−0.024359192
28	3.112029743	2.996052163	0.037267504	0.11597758	1.587177672	1.571643103	0.009787542	0.015534569
29	3.083874659	3.102107491	0.005912313	−0.018232832	1.617687941	1.589754347	0.017267604	0.027933594
		Mean	0.011931939	0.017781567			0.013451706	−0.005974264

Note: y_a = actual CO_2 intensity and y_p = predicted CO_2 intensity, AD = absolute deviation, $E_y = y_a - y_p$.

Appendix IIb
Results of evaluating predictions for CO2 emission intensities on selected optimal models.

Test samples	China				India			
	y_test	y_p	$AD_{9\text{-}5\text{-}1}$	E_y	y_test	y_p	$AD_{9\text{-}5\text{-}1}$	E_y
1	2.4742588	2.476217685	0.000791706	−0.001958885	1.616775083	1.629716932	0.008004731	−0.012941849
2	3.04116614	3.006094331	0.011532356	0.035071809	2.286198631	2.325464318	0.017175099	−0.039265687
3	3.177417239	3.150691432	0.008411173	0.026725807	2.320039421	2.355122234	0.015121645	−0.035082813
4	2.895104235	2.760091773	0.04663475	0.135012462	1.796703515	1.775702718	0.011688515	0.021000797
5	3.275505221	3.297245832	0.006637331	−0.021740611	2.462073205	2.453567944	0.003454512	0.008505261
6	3.455590533	3.433745292	0.00632171	0.02184524	2.642951673	2.608650372	0.012978407	0.034301302
7	3.158607293	3.14742997	0.003538687	0.011177323	2.186125698	2.17358942	0.005734473	0.012536278
8	2.860617925	2.796813336	0.022304478	0.063804588	1.736322211	1.737024707	0.000404588	−0.000702496
9	3.448835101	3.433540262	0.004434784	0.015294839	2.661675841	2.622687942	0.014647877	0.038987899
10	2.649050948	2.698519267	0.018673978	−0.049468319	1.647965031	1.678007653	0.018230133	−0.030042621
11	3.480602117	3.431597758	0.014079276	0.049004359	2.558507729	2.576938057	0.007203546	−0.018430329
12	3.343434723	3.383338484	0.01193496	−0.039903761	2.500872208	2.490311314	0.004222885	0.010560895
13	2.807543608	2.940877781	0.047491399	−0.133334173	2.007911528	2.002885412	0.002503156	0.005026117
14	3.014717229	2.963396239	0.017023484	0.05132099	2.060385124	2.06252965	0.001040837	−0.002144526
15	3.103787048	3.140877455	0.011950049	−0.037090407	2.144148797	2.147372376	0.001503431	−0.003223579
16	2.985550082	2.983903498	0.000551518	0.001646584	1.87473487	1.862534407	0.006507834	0.012200463
17	2.872467409	2.742890364	0.045110014	0.129577045	1.76787526	1.756087159	0.006667949	0.011788102
18	2.546181743	2.565442968	0.007564748	−0.019261224	1.591922905	1.631702439	0.024988355	−0.039779534
19	3.482958909	3.433740008	0.014131347	0.049218901	2.583927212	2.595336286	0.004415401	−0.011409075
20	3.082007333	3.052040145	0.00972327	0.029967188	2.130558157	2.132698979	0.001004817	−0.002140822
21	2.950989792	3.009949746	0.019979722	−0.058959955	2.325705068	2.335725201	0.004308428	−0.010020133
22	3.389394276	3.355821091	0.009905364	0.033573186	2.639833037	2.594654779	0.017114059	0.045178257
23	2.989548173	2.939642315	0.016693445	0.049905858	1.967782845	1.960001069	0.003954591	0.007781777
24	3.167345389	3.135017181	0.01020672	0.032328208	2.318672702	2.3458725	0.011730762	−0.027199797
25	2.827133515	2.952901646	0.044486095	−0.125768131	2.042094307	2.037462032	0.002268394	0.004632275
26	3.420218576	3.338701059	0.023834008	0.081517517	2.619170524	2.606677457	0.004769856	0.012493067
27	3.194873351	3.177663486	0.005386712	0.017209864	2.213806995	2.250382457	0.016521522	−0.036575462
28	3.065350205	3.068575734	0.001052254	−0.003225528	2.181732939	2.243029092	0.028095168	−0.061296153
29	3.239661906	3.255905802	0.005014072	−0.016243897	2.364280606	2.340317968	0.010135276	0.023962638
		Mean	0.0153586	0.011284375			0.009186077	−0.00280344

Note: y_a = actual CO_2 intensity and y_p = predicted CO_2 intensity, AD = absolute deviation, $E_y = y_a - y_p$.

Appendix IIc
Results of evaluating predictions for CO2 emission intensities on selected optimal models.

Test samples	USA			
	y_test	y_p	$AD_{9\text{-}5\text{-}1}$	E_y
1	2.574457916	2.58678845	0.004789565	−0.012330535
2	2.500005366	2.503391864	0.001354597	−0.003386499
3	2.494462043	2.504325183	0.003954015	−0.00986314
4	2.538573152	2.532567461	0.002365774	0.006005691
5	2.476437727	2.479761468	0.001342146	−0.003323741
6	2.384014635	2.401271511	0.007238578	−0.017256875
7	2.490700071	2.497796243	0.002849067	−0.007096172
8	2.530982965	2.540565841	0.003786227	−0.009582877
9	2.375633112	2.400213481	0.010346871	−0.02458037
10	2.558776552	2.559767265	0.000387182	−0.000990712
11	2.411677746	2.405923085	0.002386165	0.005754661
12	2.437965418	2.42529669	0.005196435	0.012668729
13	2.527679338	2.528293237	0.00024287	−0.000613898
14	2.498110568	2.51145488	0.005341762	−0.013344312
15	2.510632326	2.498814312	0.004707186	0.011818014
16	2.549300685	2.548590773	0.000278473	0.000709912
17	2.536693642	2.531737129	0.001953926	0.004956512
18	2.56326721	2.578462067	0.005927926	−0.015194858
19	2.402602563	2.403664347	0.000441931	−0.001061784
20	2.495939797	2.499950654	0.001606952	−0.004010857
21	2.508659751	2.495357814	0.005302408	0.013301937
22	2.438174074	2.423021859	0.006214575	0.015152215
23	2.546923136	2.545363046	0.000612539	0.00156009
24	2.497267631	2.50378933	0.002611534	−0.006521699
25	2.509936628	2.515705771	0.002298522	−0.005769143
26	2.463329963	2.44271247	0.008369765	0.020617493
27	2.481426423	2.494025421	0.005077321	−0.012598998
28	2.497681992	2.40902637	0.03549516	0.088655622
29	2.498347921	2.497707739	0.000256242	0.000640182
		Mean	0.004577094	0.001183262

Note: y_a = actual CO_2 intensity and y_p = predicted CO_2 intensity, AD = absolute deviation, $E_y = y_a - y_p$.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.03.352.

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